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Social Trading

An Analysis of Herding Behavior, the Disposition Effect, and Informed Trading among Traders under a Scopic Regime

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Social Trading: An Analysis of Herding Behavior, the Disposition Effect, and Informed Trading among Traders under a Scopic Regime

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King's College London

A thesis submitted in fulfilment of the PhD in

Finance

September 1, 2016

Dedication

I dedicate my thesis to my family. A special feeling of gratitude to my parents, Michel and Nina, for their love and support throughout this challenging endeavor. I would like to thank my brothers Nader, Karl, and Peter who were always there when I needed them. I am particularly grateful to Karl who devoted countless hours to help me develop my computer programming skills, which allowed me to handle the complexities of the large data sets used in my thesis.

I also dedicate this dissertation to my uncle Ziad for his constant support and encouragement, and to my grandparents Rafic and Samia who were excited to see me take on this challenge.

Last but not least, I dedicate my work to Nina Hashem, who is also completing a doctoral challenge of her own. Words cannot express how grateful I am for your unconditional love and support throughout this journey.

In memory of my grandmother, Mimi...

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Last but not least, I would like to thank eToro and an anonymous financial broker for providing me with their valuable proprietary data, both of which were imperative for the completion of my dissertation. As I have experienced first hand, obtaining original and high quality data is a significant obstacle for many PhD students, thus I am grateful to Dr. Alex Preda for his invaluable contacts within the financial industry.

Declaration

I hereby declare that the work presented in this thesis is original and entirely my own except where other sources are clearly cited. No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or institute.

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Number of words: 63,180

Name: ROLAND GEMAYEL

Signed Date: September 1, 2016

Abstract

Social trading is a novel phenomenon that integrates social media into online trading, forming a social trading platform (STP) that allows participants to communicate and explicitly copy each other's trades in real-time. STPs are governed by a scopic environment, which is characterized by high information transparency and constant reciprocal scrutiny by participants. We categorize participants into two main groups: trade leaders, who execute original trades and refrain from explicit copying, and investors, who solely or partially copy trades. This dissertation focuses on the former.

First, we investigate herding behavior using popular metrics developed by Lakonishok, Shleifer, and Vishny (1992) and Frey, Herbst, and Walter (2014). We find levels of, and persistence in herding behavior that exceed those found in traditional financial settings. We argue that this is due to the scopic environment governing STPs.

Second, we examine the disposition effect of trade leaders. Building on the learning hypothesis discussed by Dhar and Zhu (2006), we propose that traders learn not only from their own trades, but also from the trades of others to adjust for this behavioral bias. We find ample evidence of a weaker disposition for trade leaders on a STP compared to traders on a traditional platform. This suggests that high information transparency erodes this bias.

Third, we investigate the predictive ability of trade leaders in 16 currency pairs and three commodities. Using methods similar to Henriksson and Merton (1981) and Fishe and Smith (2012) we find that, although around 50% of traders trade profitably more than half of the time, very few possess the skill to do so in all market conditions. Nevertheless, our findings suggest that the scopic environment yields profitable short-term information that is contained in the order flow.

The concluding chapter reviews the main findings of this thesis and discusses potential future work.

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Chapter 1

Introduction

In recent years, there has been a growing interest in the role played by social media in the finance industry, mainly due to the vast amount of data collected by social platforms, and the ease with which individuals can communicate and obtain information in real-time. Researchers and practitioners have studied the relationship between the information amassed by social networks and the dynamics of financial markets, which are essentially driven by investor sentiment. For instance, Bollen et al. (2011) find that the public mood expressed through live Twitter feeds can be used to predict the daily movements in the Dow Jones Industrial Average (DJIA) with an accuracy of 87.6%. Moreover, investment firms have quickly adopted social media tools and capitalized on the opportunities brought forth by social media, such as Derwent Capital Markets, which pioneered a $40 million hedge fund that traded on market sentiment using real-time Twitter news feeds (Tweney, 2012). The innovative integration of social media into finance applications has inaugurated a new branch of literature called *social finance*, which investigates the effects of social interactions on financial outcomes (Knorr Cetina and Preda, 2004; Preda, 2007; Hirshleifer, 2015). One particular phenomenon that has attracted hundreds of thousands of traders and investors in recent years is known as *social trading*.

Social trading merges the traditional online trading model with the tools provided by social media platforms. The result is a pioneering and highly transparent marketplace called a social trading platform (STP), where participants can communicate with each other, collaborate on research tasks, and even *explicitly* copy each other's trades in real-time using a mirror trading algorithm. To elaborate, an individual can set up his account to mimic all future trades of one or multiple traders, thus any trade that is executed by a copied trader is also executed in that person's brokerage account at the same time and price. As such, STPs typically require individuals to reveal their current portfolio holdings, historical trading activities, and online social interactions to a network of participants, which is a level of transparency that is lacking in traditional financial institutions including banks (Van Roy, 2008; Giannetti, 2007; Linsley and Shrives, 2005; Flannery et al., 2004), mutual funds (Haslem, 2007), hedge funds (Goltz and Schröder, 2010; Black, 2007; Anson, 2002), and on exchanges where participants trade against each other and try to keep their strategies and holdings secret. We call the trading environment governing STPs a "scopic" regime, which signifies a situation with high information transparency where participants constantly and reciprocally scrutinize each other's actions (Knorr Cetina, 2003). In such an environment, participants do not observe each other directly, but judge each other based on the available information that is publicly disclosed every time an action is taken. One reason why participants accept to share their private information with others is because STPs encourage participants to build a track record in order to attract potential copiers, and offer remuneration packages that allow an individual to earn a performance fee based on the profits generated or on the number of copiers he has. This principal-agent relationship allows us to categorize participants into two main groups, which we call trade leaders and investors. The former typically includes experienced traders who invest the capital allocated to them by the latter in return for monetary compensation. An investor can allocate and diversify his entire capital across several trade leaders by simply opting to copy these individuals, thus having all their trades replicated in his account. The copy feature essentially gives rise to a new "socio-financial" asset, whereby the trader that is being copied may be perceived as a tradable, long-only asset whose risk and return characteristics are dependent on the financial instruments being traded, as well as on the behavior of the trader. By understanding these components, investors can then incorporate the socio-financial asset class into their portfolios in order to achieve superior risk-adjusted returns. Investing in socio-financial assets can be done by simply opting to copy the trading activity of others.

Since little research has been conducted in order to investigate the fundamental and theoretical differences that separate social trading from mainstream finance, this thesis explores this novel phenomenon in order to better understand how participants behave in a trading environment that encourages information transparency. While the research opportunities in this field are numerous, we focus on the behavior and performance of the individuals who are making the trading decisions, the trade leaders, and investigate three main research questions to better understand the characteristics of this socio-financial asset class. We examine some behavioral biases that have been studied extensively in the literature under a traditional financial setting. The first behavioral bias is herding, which is defined as the tendency of individuals or entities to copy the actions of others. The second bias is known as the disposition effect and is defined as the tendency of an individual to realize gains and hold on to losses. These biases have the potential of adversely affecting performance and increasing overall portfolio risk for investors who diversify their capital across multiple trade leaders. For instance, herding behavior can lead to homogeneity among trading styles, which consequently decreases the benefits of diversification across multiple trade leaders. Regarding the disposition effect, this bias can drive traders to realize gains prematurely, which also results in high current capital gains tax expenses. Moreover, we aim to answer the ultimate question that crosses every investor's mind, and that is "do trade leaders make informed decisions?" By answering this question, we are able to assess whether a trade leader's superior performance is due to skill or luck. Formulating the above into three main research questions, we dedicate an entire chapter to investigate each of the following:

1. Does the scopic regime governing STPs lead to levels of, and persistence in herding behavior among trade leaders that exceed those found in traditional financial environments?

2. Do trade leaders on STPs exhibit the disposition effect, or does the vast amount of information and constant investor scrutiny under a scopic regime erode this behavioral bias?

3. Do trade leaders on STPs possess superior predictive ability such that they are deemed informed, and if so, what are the trading characteristics of these informed individuals?

We begin by providing a descriptive overview of the developments in social trading and the mechanics of STPs, and we highlight some of the key differences between a scopic regime and a traditional financial setting.

1.1 Social Trading

1.1.1 Back to the Trading Floor

The concept of social trading is not entirely novel as social interactions, such as communication and physical contact, have been an integral part of open outcry financial exchanges. In trading pits, traders try to decipher the motives and emotions of other market participants and adjust their positions accordingly (Fenton-O'Creevy et al., 2012; Baker, 1984). However, these exchanges have experienced radical technological and operational changes since the introduction of electronic communications networks in the late 1960s, an innovation that relocated traders from trading floors and positioned them in front of screens (Baptiste et al., 1993). While electronic trading does have its benefits, such as increased efficiency, speed in trade execution, fewer mistakes, and lower monitoring costs, several academics have highlighted the benefits of floor trading that arise from trader interactions on the floor, which was lacking in early electronic systems (Ates and Wang, 2005). For instance, Benveniste et al. (1992) developed a model where floor participants interact prior to and after trading. Specifically, the authors find that in an equilibrium, where informed and uninformed traders are brought together, a market specialist can employ ex-post sanctions to force traders to a priori disclosure of trade information, which results in reduced information asymmetry and lower transaction costs. In a similar study, Chan and Weinstein (1993) show that floor traders develop a reputation within the pit, which is enhanced by signaling whether trades are informed or not. As such, the authors conclude that this information leads to lower transaction costs for all traders. Several academics have compared floor trading to electronic trading and found increased volatility and widening spreads after the switch was made from floor to electronic platforms (Venkataraman, 2001; Hendershott and Moulton, 2011). In addition, Ates and Wang (2005) provide an extensive comparison of the differences in operational efficiency and informational efficiency between the two types of trading settings. In particular, the authors find that floor traders 1) know who they are bidding against, 2) can select their counter-party as opposed to electronic trading, and 3) can quickly change their price quotes by a simple hand signal thus canceling any previous offer or bid, which is a very valuable option in highly volatile markets.

STPs come as a modern and innovative transition "back to the trading floor", by combining the strategic information generated from trader interactions as documented in floor trading systems, with the increased efficiency and speed of electronic trading. This amalgamation has resulted in several unique features which render STPs an entirely new trading environment. In particular, STPs are based on voluntary, full disclosure of historical trading activities and current portfolio holdings, thus allowing traders to observe and easily copy each other's actual strategies. This is in contrast to the behavior observed in pit exchanges where traders attempt to *decipher* the motives and emotions of other participants, who in turn try to hide their strategies (Fenton-O'Creevy et al., 2012). In fact, STPs encourage, and have incentivized information sharing by compensating traders based on the number of copiers they attract, or the amount of assets under management.[1] This also leads to collaboration among participants on several activities including the pooling of funds, allocation of research tasks, and sharing of valuable trading information. As a consequence, participants on STPs have access to high quality order flow as well as social information, which is essential for making informed trading decisions. This is one of the main advantages for small retail traders who seek high-quality information related to market outlook but are often faced with the challenges of a clandestine and very costly traditional investment system. Hence, STPs are a materialization of what an ideal market would look like in the eye of an investor (Kirzner, 2006), and it is this transparent environment that is attracting a larger crowd of retail traders, which would theoretically increase market efficiency and improve price discovery.

While investors always seek to gather as much information as possible in order to make informed decisions, too much information can also have adverse effects on the investment process. We discuss one potential drawback of excess information, which has been documented in the literature as information overload.

1.1.2 Information Overload

The process of decision making often requires an individual to evaluate and integrate multiple information cues simultaneously. Although the presence of information is necessary to make good decisions, excess information may impede one's ability to do so. Several early studies such as Miller (1994), Newell and Simon (1972), and Driver and Mock (1975) have presented evidence showing that the capacity of human

[1] Doering et al. (2015) discuss some of the most common compensation schemes offered by STPs.

decision makers is limited, and that people tend to make sub-optimal decisions when that limit is reached. This phenomenon is known as *information overload*, which arises when the input to a system exceeds its processing capacity (Milford and Perry, 1977). In addition to a decrease in quality of decision making (Abdel-Khalik, 1973; Snowball, 1980; Chewning Jr and Harrell, 1990), studies have also found that information overload increases the time required to make a decision and generates a higher degree of confusion regarding the decision (Cohen, 1980; Malhotra et al., 1982). As a result of lower quality, and increased time and confusion of decisions under information overload, consumers are more likely to decrease the time and effort they expend the more complex the decision (Payne et al., 1988, 1996).

Researchers have identified a number of factors that may contribute to information overload. One potential source of overload is related to how information is presented to investors. Simply bombarding investors with unstructured information about investment choices may be detrimental to a sound decision making process. Conversely, the literature on the economics of information suggests that consumers are willing to use additional information more competently if it is less costly and does not require significantly more time to acquire (Stigler, 1961; Nelson, 1970, 1974). This means that when information is readily available at a very low cost, such as on a STP, consumers are more likely to incorporate it in the decision making process. For example, studies on nutritional labeling show that standardized information printed on labels have a significant impact on how consumers use the information to make and justify their product choice (Roe et al., 1999; Ippolito and Mathios, 1990, 1994; Moorman, 1996). Since the vast amount of information on STPs can be overwhelming to individual retail traders, these platforms standardize the information and present it using a range of financial and social indicators that can be interpreted more easily by the trader. Nevertheless, the standardization process may result in loss of information, which may be of value to the trader. In addition, each platform summarizes the information differently, thus the trader should be aware of the methods and processes used by the STP provider to calculate these indicators.

Another source of information overload is related to the number of choices an individual has when faced with a decision. Studies have shown that too many options impede decision making. For instance, Iyengar and Lepper (2000) compare consumers' reactions when they were exposed to two displays of jam; the first composed of six varieties and the second with twenty-four. The authors found that, while consumers expressed more interest in the larger selection, it was the smaller selection that prompted more purchases. The results of this experiment suggest that consumers not only expend less effort when a decision becomes overwhelming, but they may also abstain from the task completely. These findings are also documented in investment behavior, where increasing the number of fund choices results in a significant decline in 401(k) contributions (Iyengar et al., 2004). Similarly, Weaver (2002) finds that the large number of options provided in Sweden's public pension program may be a key influence driving the majority of participants — over 80% of new eligible participants— to select the default pension program. In the context of social trading, investors face the decision of selecting from thousands of trade leaders to copy, which can become increasingly overwhelming given all the indicators that are provided by the platform. As such, STPs provide filtering tools and ranking algorithms, which help investors narrow the pool of potential trade leaders to copy. While this may help investors reach a decision faster, it may also drive them to copy the same trade leaders who are currently in the spotlight. This scenario is an example of unintentional herding among investors (Barber et al., 2009; Barber and Odean, 2008).

The final source of information overload we discuss is an individual's personal financial knowledge. Research has shown that there is a concave relation between information search and knowledge, such that a person with an average amount of knowledge would search the most prior to making a decision (Bettman and Park, 1980). On the contrary, experts do not feel the need to conduct substantial research because they already possess plenty of knowledge on the subject, while novice investors typically have a basic understanding and become bewildered rather quickly when faced with a choice task. It is important to note that while novice investors would benefit the most from a thorough research exercise, it is unlikely that they would undertake one. Due to this paradox, one can presume that people with average knowledge will search the most since they possess a fundamental understanding that enables them to analyze and benefit from new information. If an investor lacks the basic concepts to compare between the different investment options available to them, then the whole decision making process may become even more intimidating, thus increasing the probability they will select an easy default option.

STPs try to help participants advance their financial knowledge by providing them with a collection of material on finance principles and trading techniques.

Moreover, participants can open a demo account to get hands on experience regarding the tools and information that are provided to them by the platform. This may help individuals become more comfortable with the indicators that they can utilize in their investment decisions, thus decreasing the likelihood of experiencing information overload.

While we do not investigate information overload on STPs in this thesis, it is nonetheless important to understand that these platforms provide a vast amount of information that is unparalleled in any other financial environment. In the following section, we discuss in detail the mechanics of STPs, and highlight some of the main sources of information available to participants.

1.1.3 Mechanics of STPs

As mentioned earlier, a STP is a web-based platform that allows participants to follow, chat with, and even explicitly copy each other's trades using a mirror trading algorithm. Given this algorithm, we can categorize participants on a STP into two main groups. The first, called trade leaders, includes individuals who are supposedly experienced traders, are unique in their trading strategies and research, and make trading decisions based on their own analysis. The second group is made up of investors who entrust trade leaders with the task of managing their wealth, by explicitly copying the trades of these trade leaders. While some individuals personally invest some of their capital and allocate the rest to be managed by trade leaders, we categorize these individuals as investors throughout this thesis. The argument behind this categorization is that the copied trades do not signify autonomous and unique decisions, which may lead to biased inferences about the behavior and performance of trade leaders. For example, consider a scenario where a profitable trade leader has many copiers, and an unprofitable trade leader has very few or no copiers. If we include both trade leaders and copiers in our analysis and consider each copied transaction as an independent decision, one would conclude that the majority of individuals on the STP are skilled, when in fact only two individuals made the trading decisions. While investors may possess the ability to identify skilled trade leaders, this research question is not part of the scope of this thesis, which only focuses on trade leaders and not on the relationship between trade leaders and investors. Hence, we only examine the trades executed in the trade leaders' accounts, and we define a trade leader as an individual who has only executed original *manual* trades (i.e. refrained from explicitly copying others) throughout the period of study. In other words, executing trades manually signifies that the trader is knowledgeable, skilled, and confident enough not to resort to explicit copying.

In general, participants open brokerage accounts through the STP and start by filling out their personal information, which may be made public depending on the platform's privacy policies. After researching and back-testing a trading strategy, trade leaders start executing orders based on the signals provided by their strategies and using their own money. Some STPs, such as Ayondo, allow trade leaders to start their career as money managers using virtual money. Trade leaders aim to build a reputation on the STP, where their track record and historical trades are published on their personal profile page in real-time. STPs also publish a wide range of performance and risk metrics such as holding period return, profit and loss, volatility, maximum drawdown, number of different assets invested in, and trading frequency to name a few, as well as social indicators including the number of followers and ranking relative to others. At first encounter, it may seem irrational for a trade leader with a profitable trading strategy to disclose all his historical trades and portfolio holdings to complete strangers; however, STPs have incentivized this behavior by providing remuneration packages that are similar to those offered by investment funds. Some STPs adopt a performance-based compensation scheme where trade leaders are compensated depending on the return they generate for their copiers. Other platforms employ a *neo*-asset-based compensation scheme that links the trade leader's remuneration to the number of copiers, instead of the amount of assets under management. Doering et al. (2015) argue that the latter remuneration model decreases moral hazard as trade leaders have an incentive to build a good yet persistent track record in order to attract an increasing number of investors. This compensation scheme is adopted by eToro, the STP on which this dissertation is based. Nevertheless, a trader's choice of which STP to use may be largely dependent on the compensation scheme offered — as in the case of mutual funds (Chevalier and Ellison, 1997) — which suggests that each platform attracts a different type of audience. Hence, based on their analysis of the various compensation schemes provided by STPs, Doering et al. (2015) find that traders on the Ayondo and ZuluTrade STPs engage in riskier transactions than traders on eToro and Currensee. It is important to note that STPs can, and do change the compensation schemes they offer in order to potentially attract more traders, and to retain incumbent ones. Nevertheless, we describe the compensation package offered by eToro to participants as at the time of this study, which is 2013.

eToro compensates trade leaders with a fixed remuneration, which is a function of the number of copiers and the consistency of that trader's performance. Trade leaders on eToro may receive up to \$10 per month for each follower who has an account in excess of \$100, and the total compensation is limited to a maximum of \$10,000. In addition, the remuneration is contingent on having executed at least ten trades during a period of one month. This implies that eToro compensates traders irrespective of their performance and assets under management. However, this compensation model resembles an asset-based compensation model in the sense that trade leaders have an incentive to increase the number of copiers, which would subsequently increase their assets under management (Doering et al., 2015). It follows that a trade leader can initially adopt a highly aggressive trading strategy in order to attract copiers, after which he can switch to a more conservative strategy to retain these copiers. This is often observed in the hedge fund industry, where fund managers start off with a risk-seeking approach and later switch to a risk-averse strategy to preserve their reputation and compensation (Boyson, 2010). Nevertheless this thesis does not investigate the effects of the different types of compensation schemes on trader behavior, thus we end this discussion here.

Unlike an institutional fund management setting, the unprecedented high level of transparency offered by STPs allows investors to easily examine the past and current performance of trade leaders, which is calculated using raw data, in order to select the top trade leaders to copy. This also highlights a key attribute of STPs, in that they offer a formal ranking of traders and a range of performance measures that are constantly updated. For example, eToro ranks participants based on aggregate profit and loss, in addition to several other indicators such as minimum number of opened and winning positions in a given period, number of active days, average position duration, maximum average leverage ratio, and minimum equity invested in a given period to name a few. The STP Ayondo assigns traders to one of five career levels, where individuals can progress to the next level if they meet certain performance criteria within a given time period. This is in contrast to the non-frequent performance assessment of fund managers of traditional financial institutions such as hedge funds, who are not legally obligated to disclose their past performance and strategies, but may selectively do so in a manner that suits their interests.

The initial step for investors who do not have the time or skills to trade, but want to have their money invested by a more experienced trader, is to analyze the profile and performance of trade leaders on the network. Investors would then choose to follow a select group of traders who are judged to possess superior trading skills based on performance in prior periods, or who yield valuable information through discussions. In order to reduce skepticism regarding the authenticity of the trade leaders, investors may choose to gather additional information by getting in direct contact with them through instant messaging tools or via discussion posts.

Once the investor completes his due diligence and finds experienced trade leaders with trading styles that comply with his own investment goals, he can set up his account to automatically mimic the traders' activities in real-time using the mirror trading algorithm provided by the STP. This means that any trade executed by the trade leaders that the investor is copying is simultaneously executed in the investor's account at a price identical to that received by the trader, and without the need for manual confirmation. The investor does not need to intervene except for terminating the copying relationship. Since all trades are executed automatically, the investor can simply allocate his capital to be managed by other more experienced traders, and can diversify his investments across multiple trade leaders with different trading styles with the aim of decreasing overall portfolio volatility. Alternatively, if an investor wishes to remain involved in the trading process but does not possess the skills or time to conduct his own due diligence and analysis, he can choose to copy a specific trade after assessing the trade leader's rationale behind it. This requires the investor to manually click on the copy button that pertains to each trade, and is typically employed when the investor receives a notification in real-time about a potentially promising trade executed by others. It is important to note that while an investor can set up his account to mirror that of a trade leader, the investor still enjoys the authority to modify the copied trades as he pleases. For example, an investor might copy a market order from a trader to buy a certain currency pair, but wishes to add or alter the stop-loss level. Even though the investor changed the terms of the trade, such an action is still considered a copied trade. Nevertheless, the relationship between trade leaders and copiers is largely informal, as there are no official sanctions should trade leaders go rogue, deviate from their advertised strategy, or lose their investors' money. Similarly, investors can terminate the copying relationship at any time without facing any repercussions. Figure 1.1 illustrates the typical information and transaction flows on a STP.

Traders on STPs do not trade the actual asset, but instead open a position through a standardized contract for difference (CFD) that is written on the asset. A CFD is an electronic contract between a trader and a broker (the CFD provider), whereby the trader forgoes physical ownership of the underlying asset for a contract with the broker that provides the same economic exposure (Norman, 2009). CFDs are essentially derivative instruments that allow traders to gain exposure and speculate on the direction of the underlying asset without the need for ownership. These contracts allow the trader to take both long and short positions in the underlying asset. The payoff from the CFD is equal to the difference between the purchase price of the underlying asset and the price at which the contract is closed. Additionally, CFDs are settled daily, hence the gains and losses of open positions are realized at the end of the trading day and are subsequently rolled-over to the next trading day. A trader with a long (short) position in a CFD would profit if the price of the underlying asset rises (falls). Moreover, CFDs are traded on margin, thus the trader may deposit an amount of capital that is considerably less than the asset's notional value, potentially leading to highly leveraged positions. The trader should always keep enough capital in the account in order to cover the minimum margin requirement set by the CFD provider, otherwise the trader's positions may be liquidated.

In his book *CFDs: The Definitive Guide to Contracts for Difference*, Norman (2009) discusses some of the risks associated with (but not limited to) CFD trading, which we summarize as follows:

- **Systematic risk:** The main risk of investing in CFDs is the market or systematic risk, since CFD prices reflect the real-time bid-offer prices of the underlying asset. CFDs replicate the point-for-point movement in the underlying asset. Moreover, since CFDs are traded on margin, the leveraging effect magnifies market risk significantly, making these financial instruments popular for speculation on movements in financial markets, spread betting, or hedging existing positions. The most common way traders limit their market risk is by avoiding leveraged positions and using stop loss orders.

- **Liquidation risk:** Traders face risk of liquidation when the price of the underlying asset moves adversely to their position in the CFD (Norman, 2009). When an open position starts accruing losses, additional variation margin is required to replenish the account back to the initial margin level. Hence, the CFD provider issues a margin call to the trader to deposit additional capital to cover the potential losses should they be realized. If the trader fails to satisfy the margin requirement, the CFD provider may liquidate the positions at a loss.

- **Counter-party risk:** Many over-the-counter (OTC) derivatives deals are prone to counter-party risk. This is also applicable to CFDs where the trader could potentially incur a loss even if the underlying asset moves in a favorable direction. This risk arises from dealing directly with the CFD provider, which results in a principal-to-principal transaction rather than an agent-to-principal transaction (which is the typical case in a stock trade) (Norman, 2009). The degree of counter-party risk is defined by the credit risk of the party holding the opposite end of the deal, which in this case is the CFD provider. Counter-party risk includes the safety of the deposited capital, the probability of insolvency of the CFD provider, and operational drawbacks. A trader can mitigate, or at least decrease the likelihood of counter-party risk by checking the CFD provider's policies regarding the separation of client funds from general operating expense accounts, and the protection of client funds by an underwriter through a certificate of insurance.

Despite these risks, CFDs are a key component for the success of STPs due to the great flexibility they offer, which is crucial for the implementation of mirror trading. As such, CFDs make it possible for traders to copy each other's trades instantaneously and efficiently.

1.2 Social Trading Data

Before expanding on the research questions and findings of this thesis, we briefly present an overview of the social trading data set that is used in all three studies. We obtain a data set from the highly popular eToro STP, which includes around 63 million trades executed by all participants during 2013. eToro offers participants a wide range of assets from several markets such as foreign exchange, commodities, equities, and indices, which are listed in Table 1.1. Table 1.2 presents descriptive statistics of the full data set. As explained in the previous section, participants on eToro do not trade the actual asset, but rather open a position through a CFD that is written on the asset. eToro records the details of each trade, which include the opening and closing prices, the equity and leverage used, the direction, whether the trade was a market or limit order, and the opening and closing timestamps. The STP also records a wide range of other social information about each participant including discussion posts and active time; however, this was not made available to us due to confidentiality reasons. Since this thesis focuses on the behavior of trade leaders — who are the individuals conducting market research and executing their own trades — we apply a strict criterion where we identify an individual as a trade leader if all of his trades were entered by him personally (or his trading algorithm) into the STP throughout the period of study. Hence, we exclude from our analysis any individual who has partially or fully utilized the mirror trading feature offered by the STP. The reason is that all copied trades are simply a reflection of the original trade, thus including them in our analysis may result in erroneous statistical inferences due to the perfect correlation between these trades. Moreover, this thesis focuses on examining the effects of the scopic environment on the behavior of the trade originator, and not on the relationship between trade leaders and investors. Due to all these reasons, we only include trade leaders in our analysis, as defined above.

The final sample contains over 2.6 million trades executed by 77,476 trade leaders. Table 2.1 presents the descriptive statistics of the final sample. Currencies constitute around 83% of trades, while commodities, indices, and stocks make up around 11%, 4%, and 2%, respectively. We calculate several trading behavior characteristics, which are first averaged across all trades of each trade leader, and then across all trade leaders. In general, trade leaders engage in both long (66% of trades) and short positions. They take on high levels of risk, with a mean leverage ratio of 175 to one, and hold positions for around six days. They execute around 34 trades annually, and trade in around three different assets.

We go into further details about the social trading data set in each of the chapters depending on the data and parameters that we use.

1.3 The Socio-Financial Asset

STPs have given a new literal meaning to the phrase "investing in people". To elaborate, a trade leader can be perceived as a long-only tradable asset whose risk and return characteristics are driven by two components; the performance of the financial assets traded and the behavior of the trader. An investor can better manage risk and make informed investment decisions in socio-financial assets by understanding the behavioral biases and trading characteristics of trade leaders. As such, this thesis aims to provide insight into the behavioral characteristics of trade leaders, in order to better understand the dynamics of this novel asset class. In particular, we investigate two behavioral biases that have been widely documented in behavioral finance literature: herding behavior and the disposition effect. Moreover, we aim to answer a key question which crosses every investor's mind: do trade leaders possess superior predictive ability?

1.3.1 Herding Behavior Among Trade Leaders

Research question 1: Does the scopic regime governing STPs lead to levels of and persistence in herding behavior among trade leaders that exceed those found in traditional financial environments?

The first study we conduct investigates herding behavior among trade leaders, which is understood as the tendency of traders to end up on the same side of the market, either intentionally by mimicking the actions of others or unintentionally as a result of acting on correlated information. In an institutional context, such as in the fund industry, herding generally arises due to reputational concerns (Scharfstein and Stein, 1990; Dasgupta and Prat, 2008), remuneration based on performance benchmarking (Maug and Naik, 2011), or information differentials in the market (Bikhchandani et al., 1992; Welch, 1992). Other studies on individual investors have shown that herding appears to be primarily driven by correlated speculative motives (Dorn et al., 2008), and cognitive biases such as the representativeness heuristic, limited attention, and the disposition effect (Barber et al., 2009). Nevertheless, the general consensus in the literature is that herding levels among individual traders (Dorn et al., 2008; Barber et al., 2009; Merli and Roger, 2013) are much higher compared to the herding levels found among institutional investors (Grinblatt et al., 1995; Wermers, 1999; Wylie, 2005; Frey et al., 2014).

In our study, we investigate herding behavior among trade leaders in order to test whether constant investor scrutiny and permanent information disclosure induce high levels of herding behavior, or motivate trade leaders to adopt differentiated trading styles. Our hypothesis is that the scopic regime governing STPs increases the tendency of trade leaders to herd, and that this level of herding is greater and persists more compared to the levels found in traditional trading settings. To test this, we use a data set of transactions executed by 77,476 trade leaders during 2013 on the highly popular eToro STP, and calculate the two herding measures developed by Lakonishok, Shleifer, and Vishny (1992) (LSV henceforth) and Frey, Herbst, and Walter (2014) (FHW henceforth) to provide a range for the true level of herding as proposed by Bellando (2012). We find that the overall level of herding for the entire sample of trade leaders lies between the lower LSV measure of 16.5% and the upper FHW measure of 23.9%. These figures exceed the herding levels reported in the literature for both institutional and retail investors in traditional trading environments. Moreover, we estimate herding for sub-samples of trade leaders selected based on three trading behavior characteristics; trading intensity, leverage used, and trade size. First, we find that as the number of active trade leaders in a security increases, the level of herding decreases proportionally. We show that this is due to higher herding levels in less traded assets, which is evidence of information herding (Bikhchandani et al., 1992). Hence, trade leaders tend to herd more when market information is scarce, such that they look at other's actions as a source of valuable information. Second, we find that the relationship between herding and risk appetite is concave, which is in line with the hypothesis that overconfident traders take on more risk and tend to herd less. This is because these individuals are more confident in their own research and analysis, thus they refrain from following or mimicking others. When we examine the association between herding and trade size, we find a u-shape relation. In particular, the larger the trade size, the more a trader has to lose, thus increasing the likelihood of herding with the general consensus. As for small trades, we report a high level of herding, which may be the result of trade leader sophistication (Doering et al., 2015). Hence, small trades may be regarded as an option for the trade leader to imitate others, such that one can increase exposure if the strategy is profitable, or simply cut losses should the strategy be unprofitable. Finally, we investigate persistence in herding behavior by computing the mean contemporaneous and time-series correlations of purchase intensities based on the method presented by Barber et al. (2009). The results show a significant and almost perfect contemporaneous correlation of 98.5%, which further confirms our earlier findings on herding levels under a scopic regime. This high correlation means that one can explain almost all the variation in purchase intensities across assets of a certain random group of trade leader by looking at the purchase intensities of another random group of traders. In addition, we report significant evidence on persistence in herding across several time horizons, which fades away slowly relative to what is reported in the literature for retail traders in a traditional trading environment (Barber et al., 2009; Merli and Roger, 2013). This is in line with our argument that a scopic regime increases the likelihood of constant and perpetual herding, as individuals try to emulate the success of other participants by mimicking their current as well as historical trades.

1.3.2 Disposition Effect of Trade Leaders

Research question 2: Do trade leaders on STPs exhibit the disposition effect, or does the vast amount of information and constant investor scrutiny under a scopic regime erode this behavioral bias?

In the second study, we examine whether trade leaders exhibit the disposition effect, which is understood as the tendency to realize gains and hold on to losses (Shefrin and Statman, 1985). Under the assumption of an efficient market, a greater degree of information transparency allows market participants to make better-informed decisions. Moreover, many studies including Shapira and Venezia (2001), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), Dhar and Zhu (2006), Chen et al. (2007), Boolell-Gunesh et al. (2009), and Seru et al. (2010) show that individuals with more financial knowledge and experience exhibit a lower disposition effect compared to individuals with little or no financial knowledge. We build on this finding and propose that, as market information becomes more abundant and accessible, the disposition effect should cease to exist as participants adjust for it by learning from past trades. Since the scopic regime governing STPs requires participants to disclose all their past and current trades, trade leaders are able to learn not only from their personal historical trading activity, but also from the trades of all other participants on the network. We argue that there should be weak or no evidence of the disposition effect in an information-rich environment such as a STP, compared to a traditional trading platform.

We use a data set from the popular eToro STP with over 2.6 million trades executed by 77,476 trade leaders in 2013, in order to test whether exposure to a transparent and information-rich environment decreases the disposition effect. To do so, we adopt two empirical methods: the first, proposed by Odean (1998a), requires the calculation of the disposition spread, which is the difference between the proportion of gains realized and the proportion of losses realized, and the second is based on the Cox proportional hazards model. Moreover, we compare the results obtained for trade leaders on eToro to those of traders on a traditional online trading platform, which we call Anonymous, that does not offer integrated social trading and networking features. In general, both empirical methods show weaker evidence of the disposition effect in the scopic environment compared to the traditional financial setting, which suggests that the high degree of information transparency and the abundance of information erode this behavioral bias, although not completely. This finding contradicts what has been reported by Heimer (2015), who examines a sample of retail traders on a STP, and finds that exposure to large amounts of information leads to an increase in the disposition effect. Nevertheless, there are significant differences between our data set and the one used by the author, which we discuss in more detail in our study. Our finding concurs with the learning hypothesis discussed in the literature, where individuals on a STP can adjust for this behavioral bias by learning not only from their own historical trades, but also from the trades of others. Hence, as information on order flow becomes more accessible, trade leaders learn from these "experiences" in order to adjust for the disposition effect. Nevertheless, this does not mean that traders in a traditional financial environment do not learn from their own historical trades. Thus, we argue that traders in a scopic environment learn at a faster rate compared to traders in a traditional trading setting. Another potential explanation for the weak evidence of the disposition effect in the scopic environment is that the constant scrutiny by investors may drive trade leaders to close losing positions with almost the same propensity of closing winning positions in order to avoid holding unjustifiable paper losses. Our findings show that, by simply increasing information transparency regarding order flow, individuals can learn to avoid selling winners early and holding on to losses for too long, thus improving their performance.

1.3.3 Do Trade Leaders Make Informed Decisions?

Research question 3: Do trade leaders on STPs possess superior predictive ability such that they are deemed informed, and if so, what are the trading characteristics of these informed individuals?

In the third study, we investigate the predictive ability of trade leaders under a scopic regime in the foreign exchange and commodities markets, where individuals have access to high quality order flow data. This differentiates our study from early research done on the predictive power of technical analysis (Abbey and Doukas, 2012). It also parallels the work of Hayley and Marsh (2015) on the performance and learning ability of currency traders in a traditional trading environment. Additionally, it expands on the evidence presented by Nolte and Nolte (2016), who show that the information contained in the *aggregate* order flow of individual traders has significant predictive power. An informed trader is defined as an individual whose actions convey valuable short-term price information (Fishe and Smith, 2012). We specifically focus on the foreign exchange market, where a decentralized structure and lack of aggregate order flow data have ensued a debate of whether information differentials could allow traders to place informed trades (Goodhart, 1988; Lyons, 1997). Researchers including Lyons (2001) have argued that there exist several channels, such as order flow, through which private information plays an important role. Moreover, several early studies such as Goodhart (1988), Lyons (1997), Peiers (1997), and Covrig and Melvin (2002) discuss how private data on order flow in the foreign exchange market may result in information differentials that can be advantageously used by brokerage firms and money managers in order to gauge the fundamental value of currencies. Nevertheless, the scope of these early studies was confined due to the limited access to order flow data, which prevented in-depth analysis of individual trader behavior in the foreign exchange market (Lyons, 1995). As such, a large portion of the literature on informed trading focuses on futures traders, since information was more readily accessible from the Commodity Futures Trading Commission (CFTC), and on individual stock traders.

In the futures markets, the evidence on informed trading has been mixed. Studies such as Bessembinder (1992), Leuthold et al. (1994), De Roon et al. (2000), Wang (2001), Dewally et al. (2013), and Fishe and Smith (2012) present evidence of informed trading that supports the risk premium theory proposed by Keynes (1930) and Hicks (1946), which states that rational futures speculators would only enter the market if expected profits are positive. Other studies such as Fama and French (1987), Hartzmark (1987), Hartzmark (1991), and Kolb (1992) argue that the proportion of individuals with consistent forecasting ability is no more than one would expect due to luck. Moreover, studies on individual stock traders such as Odean (1998a,b, 1999) and Barber and Odean (2000) argue that the trading characteristics of individual investors are affected by behavioral biases, which in turn negatively impact performance.

Given the mixed empirical evidence in the literature, and despite potential behavioral biases, we expect that an environment that is highly transparent regarding order flow information should increase the overall prospects of informed trading. Thus, we aim to answer the following: are trade leaders on STPs actually informed? To investigate this, we use a data set from the highly popular eToro STP and classify over 700 thousand transactions executed by 41,072 position trade leaders — traders who keep positions open for more than one trading day — and over 1.7 million transactions executed by 48,691 intraday trade leaders in 19 different assets during 2013. These assets comprise of 16 currency pairs and three commodities. We employ empirical techniques similar to those proposed by Henriksson and Merton (1981) and Fishe and Smith (2012) in order to identify trade leaders as either position informed, intraday informed, momentum, contrarian, or uninformed. First, we use two binary profit rules based on unrealized profits (or position profits) and realized profits (or daily trading profits), separately, to assess whether position trade leaders are informed. In addition, we apply to each profit rule an unconditional test and a conditional test similar to the method proposed by Henriksson and Merton (1981) (HM test henceforth), where the former is a binomial test for the expectation of being profitable more than 50% of the time, and the latter tests whether traders are able to correctly predict future price movements in both upward and downward trending markets. Second, we analyze intraday profits and the relationship between position direction and past price movements in order to identify intraday trade leaders as either informed, momentum, contrarian, or uninformed. Since we have thousands of trade leaders, which results in thousands of test statistics, a multiple-testing problem arises where some tests may be significant due to chance. In order to control for these luck events, we use the false discovery rate (FDR) method developed by Benjamini and Hochberg (1995) with a 5% critical value. This ensures that at least 95% of trade leaders that are identified as informed are truly informed.

For position trade leaders, the unconditional test identifies around 50% of these individuals as informed, meaning that half of the position traders have profitably executed more than 50% of their trades. When we apply the HM test, the proportion of traders identified as position informed drops between 0.11% and 1.31%. This suggests that, while many position trade leaders can consistently predict price changes in a specific state of the market, very few possess the skill to do so in all market conditions. We use a series of logistic models to examine the characteristics of position informed trade leaders, where the dependent binary variable indicates whether a trade leader is informed depending on the profit rule and test used. Since the daily trading profits rule signifies the ultimate decision of the trader, and since the models based on this rule have a superior fit, we focus the discussion on these results. In particular, we find that position informed trade leaders under the unconditional test tend to use greater leverage, apply limit orders to realize gains and limit losses, use less equity per trade, are generally successful in long trades, have longer trade durations, trade less frequently, and trade in multiple assets. When we analyze the characteristics of position informed traders under the HM test, we find that these individuals use less leverage, employ limit orders effectively, use more equity per trade, are able to short-sell profitably, have long trade durations, trade more frequently, and trade in multiple assets. While both tests assess whether or not an individual is informed, each test has a different definition of "being informed." Hence, the key differences between the characteristics of informed position trade leaders under the unconditional test and under the HM test are that informed individuals who can predict price movements in any state of the market tend to 1) use less leverage, 2) use more equity per trade, 3) short-sell profitably, and 4) trade more frequently. In other words, these individuals are risk-averse, are more confident in their trading decisions, can more accurately predict the overall direction of the market, and aim to seize a larger number of potentially profitable opportunities.

With respect to intraday trade leaders, we identify around 15%, 49%, 29%, and 0.3% of the sample as informed, momentum, contrarian, and uninformed, respectively. We also examine the characteristics of these types of intraday traders using logistic regressions, and find the highest explanatory power for the intraday informed model. Specifically, we find that intraday informed trade leaders use relatively lower leverage ratios, employ limit orders to automatically realize gains and minimize losses, use more of their equity in each trade, are more successful in short trades, have relatively longer trade durations, trade more frequently, and diversify their trades in multiple assets.

Our findings suggest that an environment characterized by high transparency regarding order flow information — such as a scopic regime — can create short term information differentials that generate profitable opportunities in the foreign exchange as well as the commodities markets.

1.4 Contribution

This thesis contributes to the growing phenomenon of social trading, in order to better understand the impact of this unique trading environment on trader behavior. Our findings help traders and investors identify and mitigate behavioral biases, which constitute a significant risk component, as well as make more informed investment decisions. In particular, we first examine herding behavior among trade leaders, which has not been studied before in such a trading environment, and report significant evidence of herding. This finding is valuable to investors who wish to diversify their investments across multiple trade leaders, since herding can diminish the benefits from diversification as the correlation between the trading strategies of trade leaders converges to one. As social trading increases in popularity and becomes an integral component of portfolios of both retail and institutional investors, accounting for herding behavior becomes imperative since it affects the overall volatility of the portfolio. Hence, understanding the drivers behind this behavioral bias allows investors to manage risk more effectively. The second behavioral bias we investigate is the disposition effect, where we find weak evidence of this effect for trade leaders in a scopic environment. In contrast to what has been found by Heimer (2015), our results suggest that heightened exposure to information can decrease the disposition of traders to realize gains and hold on to losses. By learning to adjust for this bias, traders and investors benefit as they avoid paying taxes on current capital gains by keeping winning trades open, and reduce their current tax expense by realizing losses. Dhar and Zhu (2006) suggest that brokerage firms should educate their clients about the disposition effect and how to avoid it in order to adhere to a tax-efficient strategy. Nevertheless, our findings suggest that high information transparency and free access to order flow data is all that is required for traders to efficiently learn on their own to avoid this bias. The third contribution of this thesis aims to answer whether trade leaders possess superior predictive skills such that they are deemed informed, and if so, what are their trading behavior characteristics. Our findings show that, while around half of position trade leaders trade profitably more than half of the time, few of them possess the ability to correctly forecast future price changes in both good and bad market conditions. This means that investors should either try to identify trade leaders who can predict price changes in all market conditions and passively copy their trades, or adjust their exposure to trade leaders who possess predictive skill in a specific state of the market, which entails a more active investment approach.

The contributions of this thesis provide insight into the characteristics of this novel socio-financial asset class. Moreover, our findings provide a basis on which future research can investigate the relation between socio-financial assets and other asset classes, and integrate social trading into popular finance frameworks such as modern portfolio theory.

Bibliography

Abbey, B. S. and Doukas, J. A. (2012). Is technical analysis profitable for individual currency traders? *Journal of Portfolio Management*, 39(1):142–150.

Abdel-Khalik, A. R. (1973). The effect of aggregating accounting reports on the quality of the lending decision: An empirical investigation. *Journal of Accounting Research*, 11:104–138.

Anson, M. (2002). Hedge fund transparency. *Journal of Wealth Management*, 5(2):79.

Ates, A. and Wang, G. H. K. (2005). Information transmission in electronic versus open-outcry trading systems: An analysis of u.s. equity index futures markets. *Journal of Futures Markets*, 25(7):679–715.

Baker, W. E. (1984). The social structure of a national securities market. *American Journal of Sociology*, 89(4):775–811.

Baptiste, A., Kang, J. C., and Rosenfeld, R. H. (1993). Survey shows electronic systems multiplying. *Futures Industry*, 3(1):11–6.

Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2):773–806.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2):785–818.

Barber, B. M., Odean, T., and Zhu, N. (2009). Systematic noise. *Journal of Financial Markets*, 12(4):547–569.

Bellando, R. (2012). The bias in a standard measure of herding. *Economics Bulletin*, 32(2):1537–1544.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1):289–300.

Benveniste, L. M., Marcus, A. J., and Wilhelm, W. J. (1992). What's special about the specialist? *Journal of Financial Economics*, 32(1):61–86.

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies*, 5(4):637–667.

Bettman, J. R. and Park, C. W. (1980). Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis. *Journal of Consumer Research*, 7(3):234–248.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5):992–1026.

Black, K. H. (2007). Preventing and detecting hedge fund failure risk through partial transparency. *Derivatives Use, Trading & Regulation*, 12(4):330–341.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8.

Boolell-Gunesh, S., Broihanne, M.-H., and Merli, M. (2009). Disposition effect, investor sophistication and taxes: Some french specificities. *Finance*, 30(1):51–78.

Boyson, N. M. (2010). Implicit incentives and reputational herding by hedge fund managers. *Journal of Empirical Finance*, 17(3):283–299.

Chan, Y.-S. and Weinstein, M. (1993). Reputation, bid-ask spread and market structure. *Financial Analysts Journal*, 49(4):57–62.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, 20(4):425–451.

Chevalier, J. and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, 105(6):1167.

Chewning Jr, E. G. and Harrell, A. M. (1990). The effect of information load on decision makers' cue utilization levels and decision quality in a financial distress decision task. *Accounting, Organizations and Society*, 15(6):527–542.

Cohen, S. (1980). Aftereffects of stress on human performance and social behavior: a review of research and theory. *Psychological Bulletin*, 88(1):82–108.

Covrig, V. and Melvin, M. (2002). Asymmetric information and price discovery in the fx market: does tokyo know more about the yen? *Journal of Empirical Finance*, 9(3):271–285.

Dasgupta, A. and Prat, A. (2008). Information aggregation in financial markets with career concerns. *Journal of Economic Theory*, 143(1):83–113.

De Roon, F. A., Nijman, T. E., and Veld, C. (2000). Hedging pressure effects in futures markets. *The Journal of Finance*, 55(3):1437–1456.

Dewally, M., Ederington, L. H., and Fernando, C. S. (2013). Determinants of trader profits in commodity futures markets. *The Review of Financial Studies*, 26(10):2648–2683.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Doering, P., Neumann, S., and Paul, S. (2015). A primer on social trading networks— institutional aspects and empirical evidence. *Working Paper. Presented at EFMA Annual Meetings 2015.*

Dorn, D., Huberman, G., and Sengmueller, P. (2008). Correlated trading and returns. *Journal of Finance*, 63(2):885–920.

Driver, M. J. and Mock, T. J. (1975). Human information processing, decision style theory, and accounting information systems. *The Accounting Review*, 50(3):490–508.

Fama, E. F. and French, K. R. (1987). Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. *The Journal of Business*, 60(1):55–73.

Feng, L. and Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, 9(3):305–351.

Fenton-O'Creevy, M., Lins, J. T., Vohra, S., Richards, D. W., Davies, G., and Schaaff, K. (2012). Emotion regulation and trader expertise: Heart rate variability on the trading floor. *Journal of Neuroscience, Psychology, and Economics*, 5(4):227–237.

Fishe, R. P. and Smith, A. D. (2012). Identifying informed traders in futures markets. *Journal of Financial Markets*, 15(3):329–359.

Flannery, M. J., Kwan, S. H., and Nimalendran, M. (2004). Market evidence on the opaqueness of banking firms' assets. *Journal of Financial Economics*, 71(3):419–460.

Frey, S., Herbst, P., and Walter, A. (2014). Measuring mutual fund herding — a structural approach. *Journal of International Financial Markets, Institutions and Money*, 32:219–239.

Giannetti, M. (2007). Financial liberalization and banking crises: The role of capital inflows and lack of transparency. *Journal of Financial Intermediation*, 16(1):32–63.

Goltz, F. and Schröder, D. (2010). Hedge fund transparency: where do we stand? *The Journal of Alternative Investments*, 12(4):20–35.

Goodhart, C. (1988). The foreign exchange market: A random walk with a dragging anchor. *Economica*, 55(220):437–460.

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Grinblatt, M., Titman, S., and Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, 85(5):1088–1105.

Hartzmark, M. L. (1987). Returns to individual traders of futures: Aggregate results. *The Journal of Political Economy*, 95(6):1292–1306.

Hartzmark, M. L. (1991). Luck versus forecast ability: Determinants of trader performance in futures markets. *The Journal of Business*, 64(1):49–74.

Haslem, J. A. (2007). Normative transparency of mutual fund disclosure and the case of the expense ratio. *Journal of Investing*, 16(4):167–174.

Hayley, S. and Marsh, I. W. (2015). Do retail fx traders learn? *Working paper*.

Heimer, R. (2015). Peer pressure: Can social interaction explain the disposition effect? *Review of Financial Studies (Forthcoming)*.

Hendershott, T. and Moulton, P. (2011). Automation, speed, and stock market quality: The nyse's hybrid. *Journal of Financial Markets*, 14(4):568–604.

Henriksson, R. D. and Merton, R. C. (1981). On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills. *The Journal of Business*, 54(4):513–533.

Hicks, J. R. (1946). *Value and capital: an inquiry into some fundamental principles of economic theory*. Oxford: Clarendon Press, 2nd edition.

Hirshleifer, D. A. (2015). Behavioral finance. *Annual Review of Financial Economics*, 7:133–159.

Ippolito, P. M. and Mathios, A. D. (1990). Information, advertising and health choices: A study of the cereal market. *RAND Journal of Economics*, 21(3):459–480.

Ippolito, P. M. and Mathios, A. D. (1994). Information, policy, and the sources of fat and cholesterol in the us diet. *Journal of Public Policy & Marketing*, 13(2):200–217.

Iyengar, S. S., Huberman, G., and Jiang, W. (2004). How much choice is too much? contributions to 401 (k) retirement plans. *Pension design and structure: New lessons from behavioral finance*, pages 83–95.

Iyengar, S. S. and Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of Personality and Social Psychology*, 79(6):995–1006.

Keynes, J. M. (1930). *A Treatise on Money: In 2 Volumes*. Macmillan & Company.

Kirzner, E. (2006). Ideal attributes of a marketplace. Technical report, Task Force to Modernize Securities Legislation in Canada.

Knorr Cetina, K. (2003). From pipes to scopes: The flow architecture of financial markets. *Distinktion: Scandinavian Journal of Social Theory*, 4(2):7–23.

Knorr Cetina, K. and Preda, A. (2004). *The sociology of financial markets*. Oxford University Press.

Kolb, R. W. (1992). Is normal backwardation normal? *Journal of Futures Markets*, 12(1):75–91.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1):23–43.

Leuthold, R. M., Garcia, P., and Lu, R. (1994). The returns and forecasting ability of large traders in the frozen pork bellies futures market. *The Journal of Business*, 67(3):459–473.

Linsley, P. M. and Shrives, P. J. (2005). Transparency and the disclosure of risk information in the banking sector. *Journal of Financial Regulation and Compliance*, 13(3):205–214.

Lyons, R. K. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39(2):321–351.

Lyons, R. K. (1997). A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, 42(3):275–298.

Lyons, R. K. (2001). *The microstructure approach to exchange rates*. MIT Press.

Malhotra, N. K., Jain, A. K., and Lagakos, S. W. (1982). The information overload controversy: An alternative viewpoint. *Journal of Marketing*, 46(2):27–37.

Maug, E. and Naik, N. (2011). Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation. *Quarterly Journal of Finance*, 1(2):265–292.

Merli, M. and Roger, T. (2013). What drives the herding behavior of individual investors? *Finance*, 34(3):67–104.

Milford, J. T. and Perry, R. P. (1977). A methodological study of overload. *The Journal of General Psychology*, 97(1):131–137.

Miller, G. A. (1994). The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological Review*, 101(2):343–352.

Moorman, C. (1996). A quasi experiment to assess the consumer and informational determinants of nutrition information processing activities: The case of the nutrition labeling and education act. *Journal of Public Policy & Marketing*, 15(1):28–44.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, 78(2):311–329.

Nelson, P. (1974). Advertising as information. *Journal of Political Economy*, 82(4):729–754.

Newell, A. and Simon, H. A. (1972). *Human problem solving*. Prentice-Hall.

Nolte, I. and Nolte, S. (2016). The information content of retail investors' order flow. *The European Journal of Finance*, 22(2):80–104.

Norman, D. J. (2009). *CFDs: The Definitive Guide to Contracts for Difference*. Harriman House Limited.

Odean, T. (1998a). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Odean, T. (1998b). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, 53(6):1887–1934.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5):1279–1298.

Payne, J. W., Bettman, J. R., and Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14(3):534–552.

Payne, J. W., Bettman, J. R., and Luce, M. F. (1996). When time is money: Decision behavior under opportunity-cost time pressure. *Organizational Behavior and Human Decision Processes*, 66(2):131–152.

Peiers, B. (1997). Informed traders, intervention, and price leadership: A deeper view of the microstructure of the foreign exchange market. *The Journal of Finance*, 52(4):1589–1614.

Preda, A. (2007). The sociological approach to financial markets. *Journal of Economic Surveys*, 21(3):506–533.

Roe, B., Levy, A. S., and Derby, B. M. (1999). The impact of health claims on consumer search and product evaluation outcomes: Results from fda experimental data. *Journal of Public Policy & Marketing*, 18(1):89–105.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *American Economic Review*, 80(3):465–479.

Seru, A., Shumway, T., and Stoffman, N. (2010). Learning by trading. *Review of Financial Studies*, 23(2):705–739.

Shapira, Z. and Venezia, I. (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance*, 25(8):1573–1587.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.

Snowball, D. (1980). Some effects of accounting expertise and information load: An empirical study. *Accounting, Organizations and Society*, 5(3):323–338.

Stigler, G. J. (1961). The economics of information. *The Journal of Political Economy*, pages 213–225.

Tweney, D. (2012). Twitter-fueled hedge fund bit the dust, but it actually worked.

Van Roy, P. (2008). Transparency in banking. *Financial Stability Review*, 6(1):133–147.

Venkataraman, K. (2001). Automated versus floor trading: An analysis of execution costs on the paris and new york exchanges. *The Journal of Finance*, 56(4):1445–1485.

Wang, C. (2001). Investor sentiment and return predictability in agricultural futures markets. *Journal of Futures Markets*, 21(10):929–952.

Weaver, K. (2002). Reforming social security: Lessons from abroad. Technical report, Conference Proceedings from Retirement Research Consortium's Fourth Annual Conference.

Welch, I. (1992). Sequential sales, learning, and cascades. *Journal of Finance*, 47(2):695–732.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54(2):581–622.

Wylie, S. (2005). Fund manager herding: A test of the accuracy of empirical results using u.k. data. *Journal of Business*, 78(1):381–403.

Figure 1.1: This diagram shows the information and transaction flows on a STP, and the processes involved in a typical social trading environment.

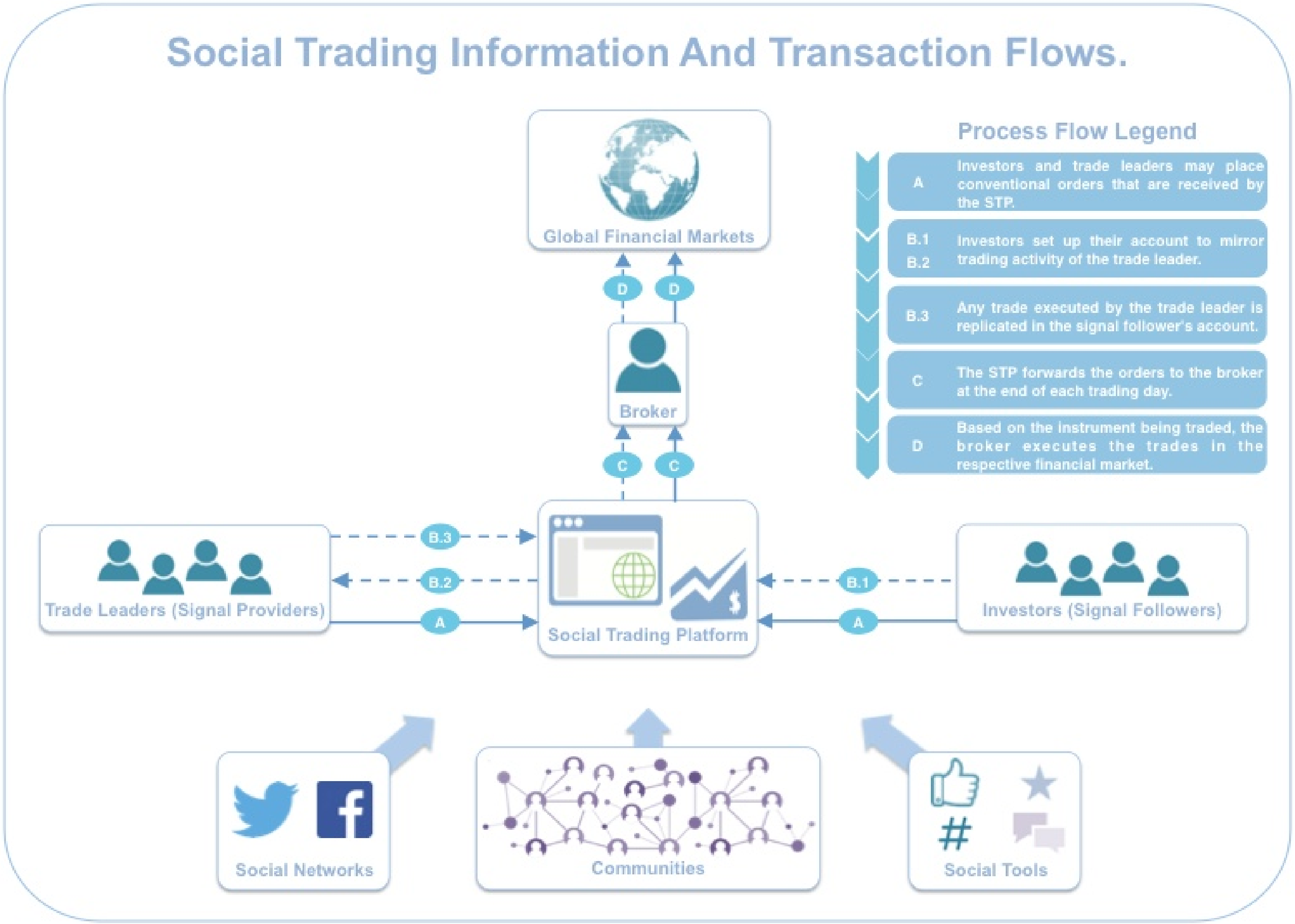

Table 1.1: **Investment Universe of the Social Trading Platform During 2013.** The following table lists all the financial instruments that were available to traders in 2013.

Currencies	Indices	Commodities	Equities		
AUD/JPY	S&P 500	Crude Oil	Alcoa	General Electric	Procter & Gamble
AUD/USD	Nasdaq 100	Gold	Apple	Google	Potash
CAD/JPY	Dow Jones 30	Silver	Adobe Systems	The Gap	Ralph Lauren
CHF/JPY	FTSE 100		Autodesk	HSBC	Banco Santander
EUR/AUD	CAC 40		American Capital Agency	The Home Depot	Starbucks
EUR/CAD	Dax 30		Amgen	Honda Motor	Siemens
EUR/CHF	ASX 200		America Movil	Harley-Davidson	SanDisk
EUR/GBP	IBEX 35		Amazon	Hewlett-Packard	Sony
EUR/JPY	SUI 30		Abercrombie & Fitch	IBM	Constellation Brands
EUR/USD	EUSTX 50		Activision Blizzard	Intel	AT&T
GBP/JPY			American Express	Johnson & Johnson	Telford Homes
GBP/USD			Boeing	JPMorgan Chase	Telecom Argentina
NZD/USD			Bank Of America	Coca-Cola	Toyota Motor
USD/CAD			Baidu	Lockheed Martin	Tripadvisor
USD/CHF			Berkshire Hathaway (B)	Linkedin	Treveria
USD/HKD			Citigroup	Las Vegas Sands	Tesla Motors
USD/JPY			Avis Budget Group	Mastercard	Grupo Televisa
BTC/USD			Caterpillar	Manchester United	Twitter
			Check Point	McDonald's	Time Warner
			Colgate-Palmolive	3M Co	Ternium
			Cisco Systems	Mobile Streams	UnitedHealth
			Chevron	Merck & Co.	Urban Outfitters
			Cemex	Microsoft	United Technologies
			Deutsche Bank	Motorola Solutions	Visa
			E I Du Pont De Nemours	Micron Technology	Vale
			WisdomTree	Noble Energy	Vodafone
			The Walt Disney Company	Netflix	Verizon
			Dr Pepper Snapple Group	NIKE	Western Digital
			DIRECTV	Nokia	Wal-Mart Stores
			Electronic Arts	NVIDIA	Western Union
			eBay	Oracle	Exxon Mobil
			Ford Motor	PBP	Yahoo!
			Facebook	PepsiCo	Zynga
			FedEx	PetSmart	
			First Solar	Pfizer	

Table 1.2: **Descriptive Statistics of All Trades During 2013.** The following table shows descriptive statistics of all trades that were opened and closed in 2013. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	62,858,725
Number of Traders	=	304,684
Financial Instruments		
Currencies	=	91.24%
Commodities	=	5.6%
Indicies	=	2.8%
Stocks	=	0.36%

	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	57.34%	168.41	4.84	207	4.0	6.5
Min	0.0%	1.0	0 (1.33 sec)	1	0.02	1
Max	100%	400.0	840.94	35,837	689	118
St.Dev.	0.313	130.75	16.61	765.75	14.72	7.1

Table 1.3: **Descriptive Statistics of Trades Executed by Trade Leaders During 2013.** The following table shows descriptive statistics of all trades executed by trade leaders during 2013. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average number of lots a trader holds. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	2,640,972				
Number of Users	=	77,476				
Financial Instruments				**Trade Close Type**		
Currencies	=	83.14%		*Manual*	=	62.76%
Commodities	=	11.21%		*Stop Loss*	=	22.04%
Indicies	=	3.60%		*Take Profit*	=	13.14%
Stocks	=	2.05%		*Rollover*	=	2.06%
	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	66.11%	175	6.08	34.18	1	3.61
Min	0.0%	1.0	0	1	0.02	1
Max	100%	400.0	347	14,672	282	71
St.Dev.	0.355	156.51	17.24	166.32	3.20	4.36

Chapter 2

Does a Scopic Regime Produce Conformism? Herding Behavior among Trade Leaders on Social Trading Platforms

Abstract

Herding has been widely studied in traditional financial markets. In this paper, we empirically examine herding behavior of a group of traders, which we label as trade leaders, in a novel financial environment called social trading. Social trading platforms (STPs) are highly transparent online markets, governed by a scopic regime, where participants are subject to constant reciprocal scrutiny. We use a data set from the popular eToro STP, with over two million transactions executed by 77,476 aspiring trade leaders, in order to test whether a scopic regime produces excess levels of herding over and above those found in other market settings. We show that the scopic regime results in excess levels of herding. Additionally, we find that herding among aspiring trade leaders is relatively high when market information is scarce, relatively low among risk-seeking traders, and that herding increases as investment size increases. Moreover, small-sized trades are used in an experimental fashion in order to emulate potentially profitable strategies. Finally, we find that herding behavior highly persists across several time periods, at much higher levels compared to what has been reported in other market environments.

2.1 Introduction

A common phenomenon that has been documented in behavioral finance literature is that investors have a tendency to herd, thus accumulating on the same side of the market. Herding behavior occurs when investors make the same decisions, either by intentionally mimicking other's investment strategies, or unintentionally as a result of acting on common information. While the latter type of herding is seen as a result of efficient markets, intentional herding has the potential to increase volatility and destabilize markets (Hirshleifer and Hong Teoh, 2003). This is due to the fact that individual investors who follow the crowd, also referred to as noise traders, have the capacity to affect asset prices since their correlated actions are systematic (Barber et al., 2009). In recent years, the notion of herding has been capitalized on by many brokerage firms, and incorporated into online trading, thus resulting in a new trading environment known as social trading.

Social trading is a novel concept that combines online trading with the tools provided by social media platforms, the result of which is a highly transparent trading marketplace known as a social trading platform (STP), where traders come together to communicate, collaborate on research tasks and trading strategies, and even *explicitly* copy each other's trading activities in real-time using a mirror trading algorithm. This system requires complete disclosure from participants regarding their real-time portfolio holdings and historical trading activities. Hence, STPs are governed by what is known as a "scopic regime", which designates a situation where participants do not observe each other directly but can see the results of each other's actions (Knorr Cetina, 2003). Consequently, participants are judged based on their actions, and are cognitively positioned in a hierarchy of status levels. One manifestation of this concept is the categorization of STP participants into two main groups: trade leaders (signal providers) and investors (signal followers or copiers), where the former presumably includes experienced traders of a superior status who manage the funds allocated to them by investors in return for monetary compensation (Doering et al., 2015). Trade leaders compete to attract potential investors by signaling their status as leaders, which is attained by executing original trades. In other words, entering trades manually into the STP signifies that the trader is knowledgeable, skilled, and confident enough not to resort to explicit copying. Investors can simply click a button to copy a single trade or all future trades of a certain trade leader, and do not need to intervene except for terminating this copying relationship. An investor can diversify his investments across multiple trade leaders with different trading styles in aim of decreasing his overall portfolio volatility. It is important to note that the investor still has the authority to modify the terms of a copied trade, such as adding a stop-loss level, in which case the trade is still considered to be copied. It follows that a trade is considered to be unique (i.e. not *explicitly* copied) only in the case where it has been manually entered by a trader into the trading platform. Moreover, the relationship between trade leaders and investors is largely informal, as there are no official sanctions should a trade leader go rogue, deviate from his advertised strategy, or lose his copiers' money.

While the principal-agent relationship between trade leaders and investors is also found in the fund industry, it differs greatly in two key aspects that render STPs a highly unique trading environment. First, STPs are based on the notion of complete disclosure of order flow data, which is particularly valuable to individual investors who seek high-quality and unbiased information for financial decision making. Moreover, order flow data is used by STPs to provide a ranking of trade leaders that is updated in real-time. This is in contrast to the non-frequent performance assessment of fund managers of traditional financial institutions such as hedge funds, who are not legally obligated to disclose their past performance and strategies but may selectively do so in a manner that suits their interests. Second, STPs encourage collaborative trading, a concept which is extremely different to what is observed on trading floors, where participants tend to keep their information and strategies private, and attempt to decipher the motives and emotions of others (Fenton-O'Creevy et al., 2012).

Very few would argue against an environment that promotes information transparency, as this increases market efficiency and price discovery. While investors on STPs can use the disclosed information to allocate their capital to the most successful trade leaders, trade leaders can similarly use this information to imitate the trading activities of their more successful peers. Such intentional herding allows traders who are new to the platform, do not have sufficient time to analyze the markets, or simply do not possess superior trading skills, to jump-start their career as money managers and start earning performance compensation by manually entering orders identical to those of successful trade leaders as they are being published in the real-time feed. This conformity can have significant consequences for investors who diversify their investments across trade leaders, since it results in higher correlation among trading strategies, which in turn diminishes the volatility-reduction benefits obtained from diversification. Nevertheless, the main puzzle we aim to solve is whether the scopic regime induces herding behavior among trade leaders, or motivates trade leaders to adopt differentiated trading styles.

Our hypothesis is that the scopic regime governing STPs increases the likelihood of herding behavior among trade leaders, and that this level of herding exceeds those found in traditional financial environments. To test this, we use a unique proprietary data set of transactions executed by 77,476 trade leaders during 2013 on the highly popular eToro STP, and compute the two herding measures developed by Lakonishok, Shleifer, and Vishny (1992) (LSV henceforth) and Frey, Herbst, and Walter (2014) (FHW henceforth) to provide a range for the true level of herding. Based on these two measures, the overall level of herding for the entire sample of trade leaders is estimated to lie between the lower LSV measure of 16.5% and the upper FHW measure of 23.9%. These figures exceed the levels presented in the literature for both institutional and retail investors in traditional trading environments. Furthermore, we estimate herding for sub-samples selected according to three trading behavior characteristics; trading intensity, risk appetite (proxied by leverage), and trade size. First, we find that as the number of active traders in a security increases, the level of herding decreases proportionally. This is shown to be due to increased herding behavior in securities that have less market information, which results in informational cascades (Bikhchandani et al., 1992). Regarding herding and risk appetite, we find evidence of an inverted u-shaped relationship, which is in line with the hypothesis that overconfident traders take on more risk and tend to herd less. When examining the association between herding and trade size, we find a u-shape relation. The larger the trade size, the more a trader has to lose, thus increasing the likelihood of following the general consensus. As for small trades, the herding level is relatively high and may be the result of trade leader sophistication (Doering et al., 2015). The idea is that small trades may be regarded as an option for the trade leader to imitate others; one can increase exposure if the strategy is profitable, or simply cut losses should the strategy be unprofitable. Finally, we investigate persistence in herding behavior by computing the mean contemporaneous and time-series correlations of purchase intensities based on the method presented by Barber et al. (2009). The results show a significant and almost perfect contemporaneous correlation of 98.5%, which further confirms our earlier findings. Moreover, we report significant evidence on persistence in herding across several time horizons, which fades away relatively slowly compared to what is reported for retail traders in a conventional trading environment (Barber et al., 2009; Merli and Roger, 2013). This is in line with our argument that a scopic regime increases the likelihood of constant herding.

The remainder of this paper is organized as follows. Section 2.2 covers the theoretical and empirical literature on herding behavior. Section 2.3 details the methodology and the two herding measures that are employed to estimate herding among trade leaders. In section 2.4, we present the data that is used along with key descriptive statistics on the trading behavior of trade leaders. Furthermore, section 2.5 is dedicated to the discussion of the findings of this study. The final section recaps the results and highlights some of the implications arising from herding on STPs.

2.2 Literature Review

To the best of our knowledge, this is the first study to examine herding behavior in a social trading context. Hence, the literature we present focuses on herding among participants in traditional financial settings, and serves as a point of comparison of herding behavior between a scopic and a traditional environment.

2.2.1 Theoretical Literature

Recent finance theory has differentiated between intentional, and unintentional or spurious herding. Intentional herding is driven by sentiment and entails the explicit imitation of the activities of others, which may lead to inefficient markets where prices fail to reflect fundamental information, in addition to increased volatility and destabilization of markets (Persaud, 2000; Hirshleifer and Hong Teoh, 2003). Nonetheless, several researchers have proposed theories and models portraying intentional herding as a rational behavior. For instance, models on informational herding are based on the notion that reliable market information is scarce. The possibility that some investors are more knowledgeable about the market may motivate a less informed investor to try and infer information from past or even current trades of others, leading to informational cascades (Bikhchandani et al., 1992; Welch, 1992). Nevertheless, Avery and Zemsky (1998) argue that if asset prices are endogenous, then they should reflect all information inherent in past transactions. As a consequence, prices should ultimately converge to reflect fundamental information, such that investors would have no incentive to follow the crowd. Another branch of literature rationalizes intentional herding as a consequence of institutional schemes such as reputation and compensation. For example, Maug and Naik (2011) find that remuneration packages may give fund managers an incentive to herd, especially when the amount of compensation received by the manager is based on performance relative to a benchmark. Similarly, studies by Scharfstein and Stein (1990) and Dasgupta and Prat (2008) examine the relationship between reputation and herding, and show that managers would sacrifice the potential to generate high returns as a trade-off against not tarnishing their reputation due to relative underperformance. In other words, fund managers may decide to disregard private valuable information and simply follow the crowd due to career concerns related to underperforming their peers (Scharfstein and Stein, 1990; Graham, 1999). Hence, when a manager's reputation and compensation are based on his performance relative to a benchmark or to the average performance of comparable peers, it becomes tempting to mimic this benchmark and sacrifice potential superior returns. As such, the more the managers are concerned about their careers, the greater the degree of conformity among them. Finally, a third reason why intentional herding may arise is due to weak market regulation or concentrated ownership (Borensztein and Gelos, 2003; Viet et al., 2008; Oehler et al., 2008).

On the other hand, unintentional herding is mainly caused by investors acting on the same or highly correlated information, leading them to arrive at similar trading decisions (Hirshleifer et al., 1994). Barber et al. (2009) conduct a study on individual investors and argue that coordinated trading is primarily driven by three behavioral factors. The first is representativeness heuristics, where investors with similar beliefs about an asset's performance persistence are likely to trade the same asset. This argument echoes the work of Tversky and Kahneman (1974) and De Bondt (1993), who argue that investors tend to make decisions where they expect the distribution of a small sample or short time series to be representative of that of the population. Moreover, another form of representativeness heuristics is discussed by Falkenstein (1996), who argues that managers may share a preference towards assets with specific risk or liquidity characteristics. The second factor is based on investors' attention, the reason being that individual investors do not have the capacity to analyze all assets available to them for investment, and may simply focus on the ones that are currently in the news spotlight. Barber and Odean (2008) and Odean (1999) hypothesize that individual investors are often faced with the dilemma of searching through thousands of stocks to invest in. Due to limited time and human capacity to analyze the entire universe of assets, investors tend to focus mostly on stocks that have caught their attention. While investors do not buy all stocks that catch their attention, their investments are highly likely to be chosen from this subset. Finally, the third factor is the disposition effect, where investors tend to avoid the regret related to selling losing investments, thus sell winning ones instead. As such, herding arises when investors sell an asset that has recently increased in value. Overall, we can identify two main categories of explanatory factors that induce herding behavior: institutional, and cognitive-psychological.

2.2.2 Empirical Literature

Measuring herding behavior can be difficult in practice (Bellando, 2012). Nonetheless, a notable paper by LSV presented a simple statistic to empirically estimate correlated trading among groups of investors, which has since become a standard measure of herd behavior despite the drawbacks it presents. The main idea underlying the LSV measure is that it analyzes the aggregate buying pressure on a specific asset for a selected subgroup of traders over a period of time. Theoretically, for the entire universe of traders, herding does not exist since the number of buyers equal the number of sellers. However, when one focuses on a subgroup of traders in a particular asset, there can be a majority of buyers or sellers, which may be attributed to herding.

LSV apply their measure to U.S. equity pension fund managers and find an overall mean herding level of 0.027. The following quote by LSV (1992: p. 30) aids in the understanding of how this figure is interpreted:

> "...it implies that if p, the average fraction of changes that are increases, was 0.5, then 52.7% of the money managers were changing their holdings of an average stock in one direction and 47.3% in the opposite direction."

Many empirical studies on herding among institutional investors have been based on the seminal work of LSV. For instance, Grinblatt et al. (1995) use a sample of 274 mutual funds from December 1974 to December 1984 and find weak evidence of herding with a mean LSV measure of 2.5%. Graham (1999) uses a more recent sample of U.S. mutual funds from 1975 to 1999 and reports a slightly higher herding measure of 3.4%. Similarly, Wermers (1999) uses the LSV measure on 20 years of U.S. mutual fund data and confirms the evidence of herding among U.S. mutual funds presented by earlier studies. In contrast to the U.S. market, researchers have estimated herding to be higher in emerging markets and several European markets such as in Germany (Walter and Moritz Weber, 2006; Frey et al., 2014; Kremer and Nautz, 2013), Finland (Kyrolainen and Perttunen, 2003), the U.K. (Wylie, 2005), France (Arouri et al., 2013), Poland (Voronkova and Bohl, 2005), and Portugal (Lobao and Serra, 2007). For example, (Lobao and Serra, 2007) estimate herding behavior among 32 equity mutual funds in Portugal between 1998 and 2000, and find a mean LSV measure of 11.38% over the three-year period. Another study by Chang et al. (2000) examines herding behavior of fund managers in the U.S., Japan, South Korea, Taiwan, and Hong Kong using the herding measure proposed by Christie and Huang (1995). The authors find evidence of herding in Taiwan and South Korea but not in other markets. Similar evidence is presented by Choe et al. (1999) who report surprisingly high herding levels in the Korean stock market in 1997. The higher level of herding in these developing markets is attributed to the stage of development of the financial system (Walter and Moritz Weber, 2006; Oehler et al., 2008), ambiguous information (Lobao and Serra, 2007), highly concentrated stock ownership (Viet et al., 2008), or incomplete market regulation especially in the area of market transparency (Borensztein and Gelos, 2003). Hence, deficiencies in corporate disclosure and low quality of information raise doubts among market participants on the reliability of market information, which consequently impedes fundamental analysis (Gelos and Wei, 2002). As such, Kallinterakis and Kratunova (2007) argue that, given weak financial regulation, investors tend to base their investment decisions on the actions of others.

LSV postulate that estimating herding across the entire population would theoretically result in no herding due to the fact that for each share bought there is a share sold. Hence, herding is more likely to be detected within subsets of investors. While all the aforementioned studies report significant evidence of herding behavior for the entire samples they use, they are nonetheless analyzing a sample of one subset, such as mutual funds, pension funds, or individual traders in a specific country, where herding behavior can exist. Given this argument, researchers have examined herding within subgroups of investors that are selected according to specific characteristics. For instance, LSV find more pronounced herding in small-cap stocks, where they estimate a herding level of 6.1% for the smallest market-cap quantile, which is in contrast to the low figure of 1.6% they report for the largest market-cap quantile. Similar evidence is presented by Voronkova and Bohl (2005). Since market capitalization of firms is often used as a proxy for the amount and quality of information available, one may infer that higher herding levels in small-cap stocks is evidence of intentional herding in situations where information is scarce. This finding is in line with the theory of information availability discussed by Wermers (1999), whereby investors are more likely to herd in situations where there is very little market information. Opposing evidence is presented by FHW, who apply both the LSV measure as well as their proposed herding measure to a data set of mutual funds specializing in German stocks from 1998 to 2004. The authors report a decreasing relationship as well as below average herding levels for smaller stocks based on the LSV measure; however they find that the number of fund managers active in a stock is positively related to market capitalization. Consequently, one should expect higher herding estimates for larger stocks due to the lower bias. The FHW measure, on the other hand, shows a u-shaped relationship with a higher level of herding for the smallest stocks. The study by Merli and Roger (2013) on individual investors also shows evidence of higher herding levels for large market capitalization stocks; however, this result is not obtained for all quarterly periods and is not robust when using the FHW measure. In particular, the authors find herding to be higher for larger capitalization stocks in 23 out of the 31 quarter when using the LSV measure, and higher for small capitalization stocks in 18 out of the 31 quarters when using the FHW measure.

Several studies, including Grinblatt et al. (1995), Wermers (1999), Wylie (2005), Lobao and Serra (2007), and Frey et al. (2014), examine herding behavior in relation to trading intensity by progressively increasing the minimum threshold for the number of transactions in each asset. The evidence presented by these studies is mixed. For instance, Grinblatt et al. (1995) report stronger evidence of herding in stocks with a high trading intensity. Similarly, Wylie (2005) reports a positive and monotonic relationship between herding and trade intensity, with herding levels of 2.5% and 9% for minimum trading intensities of five and twenty five transactions, respectively. FHW report evidence supporting these findings under the LSV measure, which they argue is due to the bias inherent in the calculation of the herding measure. However, the authors find a u-shaped association under their proposed FHW herding measure. In their study on individual investors, Merli and Roger (2013) divide their data into low, medium and high trading intensity categories, and find that the LSV herding measure is higher for stocks with a high trading volume. Nonetheless, they do not obtain the same results when using the FHW measure. On the other hand, Wermers (1999) finds little variation in the level of herding across the different thresholds for trading intensity. The author shows that herding decreases to just over 3% as trading intensity increases to more than 50 funds, and notes that the highest trading activity is found in large-cap stocks, which exhibit lower levels of herding. As such, the author argues that increasing the minimum threshold of trade intensity implicitly changes the sample to larger and more liquid stocks, which may overshadow any increase in herding that might arise from a larger number of funds active in the stocks. The results presented by Rubbaniy et al. (2014) also show a decreasing trend in the overall level of herding; however, the authors show that herding increased as the number of active traders increased from two to ten, and then again from twenty five to higher.

Other studies have investigated the relationship between herding behavior and the state of the market. For instance, Choe et al. (1999) find evidence of high levels of herding prior to the Asian crisis of 1997. Similar evidence is reported by Bowe and Domuta (2004) using data from the Jakarta Stock Exchange following the crisis, and Chiang and Zheng (2010) in developed markets not including the U.S. In addition, FHW examine herding in sub-periods and find the highest level of herding at the peak, and during the bursting of the internet bubble from 2000 to 2001. Rubbaniy et al. (2014) argue that the higher overall herding levels during times of crisis was primarily due to sell-side herding, which appeared to be driven by less risky assets. To elaborate, the authors argue that during a crisis, fund managers increase their portfolio allocation to less risky assets, such as bonds. Nonetheless, market turbulence negatively affects the prices of equities leading to a gap between strategic and actual equity allocations. To reduce this gap, fund managers should increase their allocation to equities, but are less confident in their private information due to increased market volatility. Therefore, fund managers tend to herd in order to avoid potential underperformance against their peer group resulting from high market instability. These findings suggest that heightened herding in an institutional context is situational, in the sense that it increases as uncertainty increases.

Another branch of literature focuses on herding behavior among individual or retail investors. Using a sample of daily transactions executed by more than 37,000 individual investors at a German discount broker from February 1998 to May 2000, Dorn et al. (2008) report a mean LSV estimate of 8.3%. The authors argue that the high level of herding appears to be primarily driven by correlated speculative motives. In other words, investors buy the same asset because they share the belief that this particular asset will appreciate in the future, and not because the asset is an optimal addition to a well-diversified portfolio. Moreover, a study performed by Barber et al. (2009) uses two data sets, the first composed of 66,465 investors obtained from a discount broker, and the second containing 665,544 investors at a retail broker. The authors report LSV herding measures of 6.81% and 12.79%, respectively for these data sets. Finally, Merli and Roger (2013) use a sample of 87,373 French retail investors obtained from a major European broker house for the period January 1999 to December 2006. Depending on the period used, the authors report higher herding levels compared to previous studies and conclude that herding among French individual investors falls between the lower LSV limit of 12.63% and the upper FHW limit of 21.70%.

Given the findings presented above, the general consensus in the literature is that herding behavior among individual investors is higher and more persistent as compared to institutional investors. While these studies examine herding behavior under traditional trading environments, the scopic regime governing STPs raises the following question. What happens when participants find themselves in an environment that embraces the free flow of information? Does the availability of order flow data, and constant scrutiny by investors increase the level of, and persistence in herding behavior among trade leaders over and above those found in non-scopic environments? We expect that an information-rich scopic environment, in which trade leaders are permanently scrutinized will increase their tendency to herd, as a mechanism for preserving their status. In order to empirically test this proposition, we begin by presenting the methodologies proposed by LSV and FHW.

2.3 Methodology

2.3.1 The LSV Herding Measure

LSV developed one of the most popular herding measures used in the literature, (HLSV henceforth), which estimates the tendency of traders to gather on the same side of the market in a particular asset during a given period. The idea underlying this measure is that trading (buying or selling) is a binary decision with a random distribution for all assets and periods given the hypothesis of no herding. Hence, excessive trading of an asset in a certain direction and in a given period can be interpreted as herding behavior. More specifically, herding occurs when the proportion of traders in a given asset trading in the same direction (buying or selling) is greater than the proportion of traders in the entire asset universe that are in that direction under the null hypothesis that trading decisions are independent. The HLSV measure can be expressed as:

$$HLSV_{i,t} = |\pi_{i,t} - \hat{\pi}_t| - \underbrace{E\left[\left|\frac{\tilde{b}_{i,t}}{n_{i,t}} - \hat{\pi}_t\right|; \tilde{b}_{i,t} \sim B(\hat{\pi}_t, n_{i,t})\right]}_{AF_{i,t}} \tag{2.1}$$

where $\pi_{i,t} = b_{i,t}/n_{i,t}$ is the buy proportion of traders, such that $b_{i,t}$ is the number of traders buying, and $n_{i,t}$ is the total number of active traders in security i during period t. The parameter $\hat{\pi}_t = \frac{\sum_{i=1}^{\mathbb{I}} b_{i,t}}{\sum_{i=1}^{\mathbb{I}} n_{i,t}}$ is the average proportion of traders buying relative to the total number of active traders in the entire asset universe $\mathbb{I}$ in period t, which is also the expected probability of being a buyer under the null hypothesis of no herding. $\hat{\pi}_t$ is subtracted in order to account for liquidity shocks. For example, when the majority of traders are buying securities, this does not necessarily mean that they are herding. Such a phenomenon can simply be due to the fact that these securities offer more attractive risk-adjusted returns. As investors realize and take advantage of this opportunity they are likely to have invested in the same direction, thus ending up on the same market side. Therefore, subtracting $\hat{\pi}_t$ will take into account the general shifts in and out of the market and would separate this phenomenon from herding behavior. Since the term on the left in equation 2.1 will be positive even under the null hypothesis (due to the stochastic nature of trades), the second term, $AF_{i,t}$, is an adjustment factor that corrects for this expected dispersion. The adjustment factor allows for random variation around $\hat{\pi}_t$ under the null hypothesis of independent trading decisions, and is the expected value of the left-hand term in equation 2.1, when the number of buyers $\tilde{b}_{i,t}$ is binomially distributed with probability $\hat{\pi}_t$ and $n_{i,t}$ independent draws.[1] The overall degree of herding behavior is measured by averaging $HLSV_{i,t}$ across all security-periods, i, t. A positive and significant HLSV measure indicates the existence of herding behavior among traders under the assumption of normality. This can be formally written as:

$$H_0 : HLSV \leq 0 \qquad \text{and} \qquad H_A : HLSV > 0.$$

The HLSV measure has been criticized by many academics in the literature because it suffers from several drawbacks. First, Oehler (1998) and Bikhchandani and Sharma (2000) highlight the fact that this measure only considers the number of buyers and sellers and does not take into account the volume of the asset being traded. If funds or traders are more homogeneous for large volume trades as compared to low volume trades, then assigning equal weights to all transactions will undervalue the level of herding. To illustrate this point, consider the scenario where there exists an equal number of buyers and sellers, but the amount of the security that is collectively bought is much larger than the aggregate amount sold. In this case, the HLSV measure would not detect herding behavior in the security even though it exists. Second, Bikhchandani and Sharma (2000) argue that the LSV measure captures both intentional and unintentional herding. Differentiating between these two types of herding behavior is crucial since the latter is an expected product of an efficient market, while the former has the potential of increasing volatility and destabilizing markets. Third, the HLSV measure does not allow us to identify intertemporal changes in herding behavior. While we are able to study how investors herd in a given security over time, this measure does not permit us to examine whether it is the same individuals that continue to herd in that asset. Finally, FHW and Bellando (2012) demonstrate that under the alternative hypothesis of herding, the HLSV measure has a positive value in expectations, resulting in a downward bias relative to the true herding measure that increases with the level of herding. However, these two studies show that the bias decreases as the number of active

[1] See Appendix A for an example on how to compute the adjustment factor, $AF_{i,t}$, and its effect on the $HLSV$ measure.

traders in the asset during the period increases. This is empirically proven by Merli and Roger (2013) who present evidence supporting the notion that herding increases when a minimum threshold for the number of active traders is imposed. Ignoring the adjustment factor in the HLSV measure would overstate true herding behavior since a portion of the dispersion is inevitable due to the stochastic nature of trading decisions. Nonetheless, the adjustment factor results in an over-correction of the excess dispersion which leads to a downward bias of the herding statistic (Frey et al., 2014). To overcome this issue, FHW propose an alternative measure of herding behavior, which they claim is an unbiased and consistent estimate of the true level of herding. However, Bellando (2012) shows that their measure is only unbiased in the specific scenario they consider in their simulation, where the expectations of both buying and selling assets are equal. Moreover, Bellando (2012) shows that when this condition is not satisfied, the FHW herding measure becomes biased, and is actually the upper bound of the true herding level, while the LSV measure is the lower bound. Building on this important point, we present the herding measure developed by FHW in the following section.

2.3.2 The FHW Herding Measure

FHW propose a new herding measure (labeled HFHW henceforth), which they argue is a consistent estimate of the true herding level, δ. The rationale behind this measure is similar to that of the HLSV, in the sense that it calculates the excess dispersion of trades on either side of the market (buy or sell). However, instead of using the first absolute moment, the HFHW measure employs the second moment, which is the traditional statistical measure of dispersion.[2]

Since the HFHW measure employs parameters that are similar to those used in the calculation of the HLSV measure, similar notations will be utilized to write the mathematical expression. Namely, $\hat{\pi}_t$ is the average proportion of traders buying relative to the total number of active traders in the entire asset universe $\mathbb{I}$ in period t. In addition, $b_{i,t}$ is the number of traders buying and $n_{i,t}$ is the total number of active traders in security i during period t, such that $\pi_{i,t}$ is the proportion of buy

[2]See Katti (1960) for more information on absolute moments of discrete distributions.

transactions. Given these parameters, we write:

$$\mathbb{H}^2_{i,t} = \frac{(b_{i,t} - \hat{\pi}_t n_{i,t})^2 - n_{i,t}\hat{\pi}_t(1-\hat{\pi}_t)}{n_{i,t}(n_{i,t}-1)}. \tag{2.2}$$

The numerator in equation 2.2 is the empirical variance minus the expected variance of a binomial distribution with $n_{i,t}$ number of draws and a buy probability of $\hat{\pi}_t$. It is important to note that this measure is the complement of the HLSV measure, except for using the second moment and the normalization in the denominator, which yields more desirable statistical properties.[3]

The $\mathbb{H}^2$ measure is averaged across securities and periods to obtain an estimate of the overall herding behavior. Let the set of all security-periods i, t be denoted by $\mathcal{A}$. It follows that the aggregated measure of herding can be written as,

$$\mathbb{H}^2_{\mathcal{A}} = \frac{1}{\#\mathcal{A}} \sum_{i,t\in\mathcal{A}} \mathbb{H}^2_{i,t}. \tag{2.3}$$

In order to make the aggregated herding measure comparable to the HLSV, the square root of the overall herding value is taken as follows,[4]

$$HFHW_{\mathcal{A}} \equiv \sqrt{\mathbb{H}^2_{\mathcal{A}}}. \tag{2.4}$$

The $HFHW_{\mathcal{A}}$ term is the one of interest in this study. In contrast to the $HLSV$ measure, the following statistical properties can be derived for the $HFHW$ measure and its variants in closed form.

1. $\mathbb{H}^2_{i,t}$ is an unbiased estimator of $(\delta_{i,t})^2$.

2. $\mathbb{H}^2_{\mathcal{A}}$ is an unbiased estimator of $(\delta_{\mathcal{A}})^2$.

3. $HFHW_{\mathcal{A}}$ is a consistent estimator of $\delta_{\mathcal{A}}$ as $\#\mathcal{A} \to \infty$.

[3]FHW show that equation 2.2 can be re-written in a manner similar to HLSV such that,

$$HLSV_{i,t} = |\pi_{i,t} - \hat{\pi}_t| - E\left[\left|\frac{\tilde{b}_{i,t}}{n_{i,t}} - \hat{\pi}_t\right|\right]$$
$$\mathbb{H}^2_{i,t} = \left((\pi_{i,t} - \hat{\pi}_t)^2 - E\left[\left(\frac{\tilde{b}_{i,t}}{n_{i,t}} - \hat{\pi}_t\right)^2\right]\right) \times \frac{n_{i,t}}{n_{i,t}-1}$$

where $E[.]$ is the expected value under the hypothesis of no herding.

[4]When the $\mathbb{H}^2$ term is negative, which is possible for low number of observations and a minimal level of herding, the square root of the absolute value of $\mathbb{H}^2$ multiplied by -1. However, such a case rarely occurs given the high levels of herding and the large number of observations in empirical studies.

The hypothesis that we test can be expressed as:

$$H_0 : HFHW \leq 0 \qquad \text{and} \qquad H_A : HFHW > 0.$$

While HLSV is biased under the alternative hypothesis of herding, but performs well under the null hypothesis, the opposite is true for HFHW. FHW argue that given a small number of traders n, HFHW would exhibit a downward bias which stems from the non-linearity of taking the square root of the unbiased estimator $\mathbb{H}^2$. Additionally, HFHW is not reliable under the null hypothesis of no herding; however it is a consistent estimator if there exists a significant level of herding in the sample. If significant herding behavior is confirmed using the HLSV or $\mathbb{H}^2$ measures, then the level of herding can be estimated consistently using the HFHW statistic.

One criticism of the HFHW measure is that it is only unbiased in the particular environment considered by the authors, where $\hat{\pi} = 0.5$ (i.e. where the probability that a stock is bought is equal to the probability that it is sold). Bellando (2012) argues that when the probability of no herding is not null, HFHW exhibits an upward bias, which arises when aggregating the $\mathbb{H}^2$ measure across all security-periods i, t as expressed in equation 2.3. In particular, the bias occurs due to the fact that the square root of a sum is not (except in unique cases) the sum of the square root of estimates. While it is practically impossible to compute the true herding level, the author shows that this value is bounded by the lower HLSV estimate and the upper HFHW estimate.[5]

2.4 Data

The data set used in this study is obtained from eToro, one of the largest and most popular STPs, and contains over 63 million transactions executed by all trade leaders and investors during 2013. eToro offers traders a wide range of assets from

[5] Bellando (2012) proposed a modified version of the HFHW estimate which, given the real probabilities of buying and selling a specific security, would provide the theoretical true herding estimate. The corrected estimate, labeled HFHWC, can be generally written as,

$$HFHWC = \frac{1}{\sqrt{\frac{1}{4\hat{\pi}_t^{buy}} + \frac{1}{4\hat{\pi}_t^{sell}}}} HFHW \tag{2.5}$$

where $\hat{\pi}_t^{buy}$ and $\hat{\pi}_t^{sell}$ are the probabilities of buy-side and sell-side categories of securities. The author states that the corrected method is not very tractable since it requires prior knowledge of the herding level and the probabilities $\hat{\pi}_t^{buy}$ and $\hat{\pi}_t^{sell}$, which may be difficult to estimate.

several markets, including currencies, commodities, and equities, which are listed in Table 1.1. Participants on eToro do not trade the actual asset, but instead open a position through a standardized contract for difference (CFD) that is written on the asset. A CFD is an electronic contract between a trader and a broker (the CFD provider), whereby the trader forgoes physical ownership of the underlying asset for a contract with the broker that provides the same economic exposure (Norman, 2009). CFDs are essentially derivative instruments that allow traders to gain exposure and speculate on the direction of the underlying asset, without the need of ownership. These contracts are traded on margin, thus the trader may deposit an amount of equity that is considerably less than the asset's notional value, potentially leading to highly leveraged positions. The STP records the details of each CFD transaction, including the opening and closing prices, the amount bought or sold, the leverage used, the direction, as well as the time-stamp of each trade. Since this study is focused on the herding behavior among trade leaders, we apply a strict criterion where we only select traders whose transactions were all entered manually into the STP during 2013. It is important to note that many traders can have a mix of manual as well as explicitly copied trades; however, these traders are not considered to be trade leaders but rather investors who reserve a portion of their capital for personal trading. Executing only manual trades signals potential superior status, confidence, and skill, whereby the trade leader is seen by investors as a unique and autonomous entity with the ability to add value.

The final sample encompasses over 2.6 million transactions executed by 77,476 trade leaders. These transactions can be categorized according to the asset traded as follows: currencies constitute the majority with 83.14% of transactions, whereas commodities, indices, and stocks make up 11.21%, 3.6% and 2.05%, respectively. Moreover, we calculate several behavioral trading characteristics, which are first averaged across all transactions for each trade leader, and then averaged across all trade leaders. These statistics are presented in Table 2.1. On average, 66.11% of transactions are long positions, with a mean leverage ratio of 175. These results are consistent with the notion that trade leaders are considered to be sophisticated, such that they enter in both long and short positions (Engelberg et al., 2012, 2014), and are confident enough in their trading abilities to employ high levels of leverage. Regarding the average duration of a trade, trade leaders keep transactions open for approximately 6 days, which indicates that they are aware of the impact of rollover costs on profits associated with keeping positions open over the weekend. Similarly, the average number of annual trades for trade leaders is around 34, which is much lower than that of the entire sample of participants — the average for the entire sample is 207 —, indicating that trade leaders account for trading costs when optimizing their strategies. Finally, we find that trade leaders on average trade in around three to four different assets, which suggests that they tend to be specialized in specific assets.

2.5 Results

In order to test whether the scopic regime governing STPs leads to excess herding, we compute the HLSV and HFHW measures for the entire sample of trade leaders and compare the results to herding levels among fund managers and retail investors in traditional trading environments. The results presented in the first row of Table 2.2 (i.e. where $n \geq 0$ and there are no restrictions on trade intensity) show that the level of herding among trade leaders ranges between the lower HLSV limit of 16.5% and the upper HFHW limit of 23.9% (based on monthly periods), and is significantly higher compared to results from studies on institutional and retail investors. Since trade leaders are essentially retail traders who happen to trade on a STP instead of a traditional online platform, a comparison between trade leaders and individual investors is more appropriate. As a recap of the literature on individual investors, Dorn et al. (2008) estimate a mean herding level of 8.3%, Barber et al. (2009) find herding levels of 6.81% and 12.79% for each of the data sets they use, and Merli and Roger (2013) conclude that herding among French individual investors falls between the lower HLSV limit of 12.63% and the upper HFHW limit of 21.70%.

The evidence we present clearly indicates that herding behavior among trade leaders on STPs is much higher compared to both institutional and individual investors on non-STPs. While a proportion of herding among trade leaders — who are essentially retail traders — may be explained by behavioral factors such as the representativeness heuristic, limited attention, and the disposition effect as explained by Barber et al. (2009), the excess herding may be attributed to the scopic regime of STPs.

In the following sections, we examine herding in sub-samples of trade leaders selected according to three behavioral factors: trading intensity, leverage, and trade size.

2.5.1 Herding and Trading Intensity

We estimate the HLSV and HFHW herding measures using the full sample of trade leader transactions based on quarterly, monthly and weekly subperiods. The process is then repeated by applying various thresholds to the minimum number of trades in each security. A higher minimum threshold implies greater trading intensity in the sample. Table 2.2 shows the results of both herding measures, in addition to the number of security-periods and the average number of trades for each threshold. We do not report the weekly results for all the analyses conducted in this paper, since they provide the same conclusion as the quarterly and monthly estimates. As expected, the HFHW estimates are higher than the HLSV estimates for all threshold levels. A more interesting finding is the relationship between herd level and the number of traders active in a security. In particular, we observe that as the number of traders active in a security increases, both the HLSV and HFHW herding measures decrease linearly. This finding is similar to the evidence presented by Wermers (1999), and may be explained by the theory of information availability and informational cascades (Bikhchandani et al., 1992; Welch, 1992). Securities with low liquidity are generally not extensively covered by analysts, resulting in scarcity of information regarding these securities. Due to the lack of sufficient information, these securities attract a small number of active traders who may turn to interpreting other traders' transactions as a scarce source of valuable information. By doing so, herding levels in illiquid securities are likely to be higher compared to those where information is more abundant. In order to test this hypothesis, we re-estimate the herding measures at the various thresholds; however, we use a sample containing only the most liquid securities. This sample includes the major currency pairs: EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/JPY, USD/CHF, and AUD/USD. The estimates for the HLSV and HFHW measures for all thresholds using quarterly (monthly) sub-periods are constant and equal to 0.089 (0.098) and 0.120 (0.133), respectively. As a consequence, the high herding levels found in less liquid securities can be attributed to lack of sufficient market information.

2.5.2 Herding and Leverage

The second relationship that we examine is between herding and the degree of leverage used by trade leaders, which is an indication of their risk appetite. We estimate HLSV and HFHW for the different leverage subgroups using quarterly, monthly, and weekly subperiods. The results presented in Table 2.3 show that the relationship between the degree of leverage and both herding measures follows an inverted u-shape. In particular, highly risk-averse traders such as those with a leverage ratio of 2 to 1 exhibit relatively lower herding levels compared to less risk-averse traders (or medium risk takers with leverage ratios between 10 to 1 and 50 to 1). One possible reason for this result is the scarcity of observations in the lowest leverage subgroups. By looking at the last two columns of Table 2.3, specifically for the leverage ratios 2 to 1 and 5 to 1, it is clear that the average number of trades are relatively low compared to the figures shown for other leverage ratios. As a consequence, FHW show using Monte Carlo simulation that, unless the number of trades in a security-period is extremely large, then both herding measures will be biased downward. Another behavioral explanation for low herding among trades with low leverage, is that these trades can be seen as experimental, where trade leaders try out new strategies without taking on too much risk.

With respect to herding behavior of risk-seeking trade leaders, the results show that herding levels are lower than those of their medium-risk counterparts. This phenomenon is well documented in the literature by studies such as Scharfstein and Stein (1990) and Gümbel (2005), who find that fund managers who are likely to herd are more risk averse than non-herding managers. The idea here is that overconfident traders take on more risk because they tend to underestimate risk and overestimate the conditional expected return from their trading strategies (Odean, 1998; Hirshleifer and Luo, 2001). Analogously, it follows that high risk takers are overconfident in their trading skills and strategies, hence they tend to herd less with each other (De Long et al., 1990, 1991; Hirshleifer and Luo, 2001).

Being risk-prone and overconfident does not necessarily mean that one is more knowledgeable. Highly leveraged trades can be seen as "black swan" trades, which are executed by traders who have a particularly high level of confidence and tolerance for volatility. This can deter other trade leaders from herding, since they would suffer great financial losses and taint their reputation in case the black swan trade goes sour. The safest herding strategy to preserve status as a trade leader would be to stand in the middle of the risk spectrum, and imitate moderately risky trades where a loss will not have a detrimental impact on reputation. In addition, allowing highly leveraged traders to fly solo would work to one's advantage when their trades accrue losses, as this thins out the competition among trade leaders.

2.5.3 Herding and Trade Size

The third analysis examines the variation in herding depending on trade size. Many studies on hedge funds and mutual funds have shown that as fund managers mature, they are more likely to herd because they have more to lose in terms of compensation (Boyson, 2010; Graham, 1999; Scharfstein and Stein, 1990). Following this reasoning, we propose that traders with larger positions are likely to herd more in order to avoid the disappointment of underperforming their peers.

In order to test this proposition, we first divide the data into quintiles based on trade size, then we compute the herding measures for each quintile using quarterly, monthly, and weekly subperiods. Quintile 1 encompasses the trades with the largest trade sizes while quintile 5 contains the smallest trades. The results presented in Table 2.4 show a u-shaped association between trade size and herding. In particular, as trade size decreases (from quintile 1 to quintile 4) so does the level of herding. This finding is consistent with our proposition that the larger a trader's investment, the more he has to lose, and the more he is likely to herd. With respect to the smallest trade size quintile, herding is estimated to be relatively high. This may be attributed to trade leader sophistication. This argument draws from the conclusion of Doering et al. (2015) who find significant correlations between social trading returns from eToro and almost all the hedge fund trading strategies they consider, indicating that eToro attracts relatively more experienced traders. Hence, this study contends that herding behavior for the smallest trade size quintile may be interpreted as follows: a trader invests a very small portion of his wealth to buy an option that allows him to mimic the trades of others. Similar to a financial option, the downside risk is limited to the trader's small investment, while there is unlimited upside potential. This real option allows the trader to either continue herding and increase his exposure to the other trader if the copied strategy performs well, or to simply cut his losses in case the strategy performs poorly. Nevertheless, Doering et al. (2015) do not test the significance of their model on sub-samples of traders with different trade sizes, thus further analysis is required in order to understand the relationship between trader sophistication and trade size.

2.5.4 Persistence in Herding

In our final analysis, we adopt an approach similar to that applied by Barber et al. (2009) to test whether trade leaders' trading decisions are correlated. Moreover, we examine the persistence in herding such that persistence exists if the autocorrelation of purchase intensities $\pi_{i,t}$ is high. In other words, a high (low) purchase intensity in asset i at time t is followed by a high (low) purchase intensity in future periods.

To conduct this analysis, we divide the data set into two equally sized random groups of traders, labeled G_1 and G_2, respectively. For each of the two groups, we calculate the monthly purchase intensities for every asset, which are denoted by $\pi_{i,t}^{G_1}$ and $\pi_{i,t}^{G_2}$, respectively. We subsequently calculate the contemporaneous correlations between the purchase intensities, resulting in a time-series of 12 monthly correlations. If the traders' trading decisions are independent, then no correlation between $\pi_{i,t}^{G_1}$ and $\pi_{i,t}^{G_2}$ is expected. To test this hypothesis, we calculate the average mean contemporaneous correlation, followed by a test of significance to check whether the correlation is different from zero. Barber et al. (2009) explain that the null hypothesis of no correlation between the purchase intensities is synonymous to the null hypothesis of no herding behavior when applying the HLSV and HFHW measures. While this analysis does not allow us to differentiate between intentional and unintentional herding, it simply indicates whether or not trading decisions are correlated.

Next, we measure the degree of persistence in herding behavior by calculating the monthly correlations between the purchase intensities at time t and $t + \tau$, where $\tau = 1 \rightarrow 11$. Recall that the contemporaneous correlations to test the null hypothesis of no herding are obtained by setting $\tau = 0$. When $\tau > 0$, then the degree of persistence in herding behavior is computed. For example, by setting $\tau = 1$, the correlation between the purchase intensities between month t and the consecutive month $t + 1$ is computed. This results in a time series of 11 correlations that are averaged to obtain the degree of persistence for a time horizon equal to 1 period. This calculation is repeated with different values for τ, and is conducted on each of the two random groups of traders, separately. Moreover, this calculation is also applied to both groups together in a manner similar to the analysis of the contemporaneous correlations, which is essentially the specific scenario where $\tau = 0$. In other words, we calculate the correlations between the purchase intensities of the first group of traders G_1 at time t, and those of the second group G_2 at time $t + \tau$.

Table 2.5 presents the results for both the contemporaneous and time-series correlations of the purchase intensities. The first row of the table (where $\tau = 0$) shows that the contemporaneous correlation of $\pi_{i,t}$ between G_1 and G_2 is 98.5%. This figure indicates almost perfect correlation between the trading decisions of the two groups of traders in a given month, and is around 14% and 24% higher than the results reported by Merli and Roger (2013) and Barber et al. (2009), respectively. This correlation, as explained by Barber et al. (2009), has an intuitive interpretation, such that the square of the contemporaneous correlation is equivalent to the R^2 obtained from regressing the purchase intensities of G_1 on those of G_2. In our analysis, the $R^2 = 97.02\%$, meaning that we can explain almost all the variation in the purchase intensities of one group of trade leaders by knowing the purchase intensities of another group. This confirms our earlier findings on herding behavior based on the HLSV and HFHW measures.

The remaining results show the correlations between the purchase intensities at time t and $t + \tau$, for $\tau = 1 \rightarrow 11$. In general, all the correlations are significant as indicated by their respective t-statistics. Moreover, the correlations obtained in this study are much larger than those reported by Merli and Roger (2013) and Barber et al. (2009). For instance, given a time horizon of $\tau = 1$, Merli and Roger (2013) report correlations of 30.27% and 31.50%, and Barber et al. (2009) report values between 46.7% and 48.2% for the large discount broker and 55.8% and 58.6% for the large retail broker. On the other hand, our study shows much higher correlations ranging between 91.3% and 93.0% for the same time horizon. Similar results are found for the rest of the time horizons, indicating that persistence in herding behavior is significantly higher among trade leaders on STPs. Another important finding of this analysis is that persistence fades away very slowly compared to the results reported by both Barber et al. (2009) and Merli and Roger (2013). For example, we find that the correlations between groups 1 and 2 are equal to 80.0% and 69.9% for the two time horizons $\tau = 6$ and $\tau = 11$, respectively. Barber et al. (2009) report correlations of 17.9% and 10.3% for the same time horizons at the large discount broker, and 31.8% and 23.2% at the large retail broker, while Merli and Roger (2013) report correlations of 8.21% and 3.55% for the two time horizons, respectively.

The strong persistence in herding over the various time horizons indicates that this phenomenon is not due to momentary events of increased uncertainty. Herding remains relatively high even for a horizon of 11 months. The significant difference in the rate of decay of persistence in herding behavior over time between trade leaders on STPs and retail investors on non-STPs indicates that social trading, through its scopic regime, has an additional conformism effect on participants. Trade leaders do not imitate each other at specific points in time, but rather do so continuously across multiples time periods. This is possible since STPs publish current as well as historical order flow data, which can be easily accessed by all STP participants. Therefore, persistence in herding behavior is expected to be high and to fade away slowly as traders may be tempted to replicate the past trades of others, which are conveniently documented by the STP.

2.6 Conclusion

This is the first paper to investigate herding behavior of traders under a scopic environment. Using a unique data set of 77,476 trade leaders obtained from the STP eToro, we examine the herding behavior of trade leaders by computing the measures proposed by LSV and FHW to provide a range for the true level of herding. In general, the overall level of herding based on the entire sample of trade leaders exceeds the estimates presented in the literature for both institutional as well as retail investors in traditional financial environments. The excess level of herding is attributed to the scopic regime governing STPs. Moreover, we compute the herding measures for sub-samples of trade leaders chosen according to three trading behavior characteristics. First, we find that as the number of active traders in a security increases, herding decreases linearly. This finding can be explained using the theory of information availability, such that herding is expected to be higher in less liquid securities where information is scarce. Second, the association between herding and the degree of leverage used is found to follow an inverted u-shape relation. Highly risk averse traders exhibit lower herding levels compared to medium leverage traders, which may be attributed to the scarcity of observations that bias the herding measures. Regarding risk-seeking trade leaders, herding levels are also found to be lower than those of their medium-risk counterparts. This may be related to overconfidence of risk-seeking traders who tend to have more confidence in their own trading strategies and skills. As such, the scopic regime encourages herding mostly among medium-risk takers, where there is a modest trade-off between maintaining status quo as leaders and maximizing risk-adjusted returns. The third relation that we examine is between herding and trade size, where we find that trade leaders who have more to lose are more likely to herd. The u-shaped relationship obtained indicates that, as trade size decreases, so does the level of herding. Moreover, herding is high for the smallest sized trades, which may be due to trade leaders using very small portions of their capital to try and emulate potentially profitable trades. Finally, we investigate persistence in herding behavior, and find high levels of persistence across several time horizons. Additionally, we show that persistence in herding among trade leaders fades away much slower compared to herding among traders in traditional trading environments. This difference may be attributed to the high degree of transparency on STPs, which grants traders access to each other's trading activities. On a theoretical level, we add to the literature on herding by showing that status concerns impact herding not only at the institutional level, but also at the retail level and in a highly informal environment. The scopic regime of STPs, with its permanent disclosure of information, produces herding levels among trade leaders that exceed and persist more than those documented in non-scopic environments for similar categories of retail traders.

The high level of, and persistence in herding behavior among trade leaders on STPs unveils several implications. From a macroeconomic perspective, it has been argued that intentional herding increases market volatility due to the high correlation among trades (Hirshleifer and Hong Teoh, 2003; Barber et al., 2009). This issue may quickly materialize as STPs become more popular among retail traders, while regulators remain largely absent from monitoring these platforms and setting pre-emptive protocols to protect naïve investors. With respect to investors who wish to diversify across multiple trade leaders, the benefits of diversification are greatly diminished in the presence of herding. This is because trade leaders who herd are essentially trading the same assets in the same direction and at the same time. Hence, investors should proceed with caution and take into account herding behavior when selecting the trade leaders they wish to allocate their funds to. Finally, STPs offer performance compensation programs to trade leaders based on the number of copiers they attract or on their actual trading performance. While trade leaders who are authentically skilled should be compensated for their efforts and added value, others who simply herd should not be compensated similarly, since this may drive truly skilled traders to exit the social trading network.

Bibliography

Arouri, M. E. H., Bellando, R., Ringuedé, S., and Vaubourg, A.-G. (2013). Herding in french stock markets: Empirical evidence from equity mutual funds. *Bankers, Markets & Investors*, (127):42–58.

Avery, C. and Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. *American Economic Review*, 88(4):724–748.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2):785–818.

Barber, B. M., Odean, T., and Zhu, N. (2009). Systematic noise. *Journal of Financial Markets*, 12(4):547–569.

Bellando, R. (2012). The bias in a standard measure of herding. *Economics Bulletin*, 32(2):1537–1544.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5):992–1026.

Bikhchandani, S. and Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers*, 47(3):279–310.

Borensztein, E. and Gelos, G. (2003). A panic-prone pack? the behavior of emerging market mutual funds. *IMF Staff Papers*, 50(1):43–63.

Bowe, M. and Domuta, D. (2004). Investor herding during financial crisis: A clinical study of the jakarta stock exchange. *Pacific-Basin Finance Journal*, 12(4):387–418.

Boyson, N. M. (2010). Implicit incentives and reputational herding by hedge fund managers. *Journal of Empirical Finance*, 17(3):283–299.

Chang, E. C., Cheng, J. W., and Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance*, 24(10):1651–1679.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, 34(8):1911–1921.

Choe, H., Kho, B.-C., and Stulz, R. M. (1999). Do foreign investors destabilize stock markets? the korean experience in 1997. *Journal of Financial Economics*, 54(2):227–264.

Christie, W. G. and Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market?. *Financial Analysts Journal*, 51(4):31–37.

Dasgupta, A. and Prat, A. (2008). Information aggregation in financial markets with career concerns. *Journal of Economic Theory*, 143(1):83–113.

De Bondt, W. F. (1993). Betting on trends: Intuitive forecasts of financial risk and return. *International Journal of Forecasting*, 9(3):355–371.

De Long, B., Shleifer, A., Summers, L., and Waldmann, R. (1991). The survival of noise traders in financial markets. *Journal of Business*, 64(1):1–19.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4):703–738.

Doering, P., Neumann, S., and Paul, S. (2015). A primer on social trading networks— institutional aspects and empirical evidence. *Working Paper. Presented at EFMA Annual Meetings 2015.*

Dorn, D., Huberman, G., and Sengmueller, P. (2008). Correlated trading and returns. *Journal of Finance*, 63(2):885–920.

Engelberg, J., Reed, A. V., and Ringgenberg, M. (2014). Short selling risk. *Western Finance Association (WFA).*

Engelberg, J. E., Reed, A. V., and Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2):260–278.

Falkenstein, E. G. (1996). Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *Journal of Finance*, 51(1):111–135.

Fenton-O'Creevy, M., Lins, J. T., Vohra, S., Richards, D. W., Davies, G., and Schaaff, K. (2012). Emotion regulation and trader expertise: Heart rate variability on the trading floor. *Journal of Neuroscience, Psychology, and Economics*, 5(4):227–237.

Frey, S., Herbst, P., and Walter, A. (2014). Measuring mutual fund herding — a structural approach. *Journal of International Financial Markets, Institutions and Money*, 32:219–239.

Gelos, G. and Wei, S.-J. (2002). Transparency and international investor behavior. *IMF Working Papers*, 2(174).

Graham, J. R. (1999). Herding among investment newsletters: Theory and evidence. *Journal of Finance*, 54(1):237–268.

Grinblatt, M., Titman, S., and Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review*, 85(5):1088–1105.

Gümbel, A. (2005). Herding in delegated portfolio management: When is comparative performance information desirable? *European Economic Review*, 49(3):599–626.

Hirshleifer, D. and Hong Teoh, S. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, 9(1):25–66.

Hirshleifer, D. and Luo, G. Y. (2001). On the survival of overconfident traders in a competitive securities market. *Journal of Financial Markets*, 4(1):73–84.

Hirshleifer, D., Subrahmanyam, A., and Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *Journal of Finance*, 49(5):1665–1698.

Kallinterakis, V. and Kratunova, T. (2007). Does thin trading impact upon the measurement of herding? evidence from bulgaria. *Ekonomia*, 10(1):42–65.

Katti, S. K. (1960). Moments of the absolute difference and absolute deviation of discrete distributions. *The Annals of Mathematical Statistics*, 31(1):78–85.

Knorr Cetina, K. (2003). From pipes to scopes: The flow architecture of financial markets. *Distinktion: Scandinavian Journal of Social Theory*, 4(2):7–23.

Kremer, S. and Nautz, D. (2013). Short-term herding of institutional traders: New evidence from the german stock market. *European Financial Management*, 19(4):730–746.

Kyrolainen, P. J. and Perttunen, J. (2003). Investors' activity and trading behavior. In *EFA 2002 Berlin Meetings Presented Paper, EFMA Helinski Meetings*.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1):23–43.

Lobao, J. and Serra, A. P. (2007). Herding behaviour: Evidence from portuguese mutual funds. In Gregoriou, G. N., editor, *Diversification and Portfolio Management of Mutual Funds*, pages 167–197. Springer.

Maug, E. and Naik, N. (2011). Herding and delegated portfolio management: The impact of relative performance evaluation on asset allocation. *Quarterly Journal of Finance*, 1(2):265–292.

Merli, M. and Roger, T. (2013). What drives the herding behavior of individual investors? *Finance*, 34(3):67–104.

Norman, D. J. (2009). *CFDs: The Definitive Guide to Contracts for Difference*. Harriman House Limited.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5):1279–1298.

Oehler, A. (1998). Do mutual funds specializing in german stocks herd? *Finanzmarkt und Portfolio Management*, 12(4):452–465.

Oehler, A., Rummer, M., and Wendt, S. (2008). Portfolio selection of german investors: On the causes of home-biased investment decisions. *Journal of Behavioral Finance*, 9(3):149–162.

Persaud, A. (2000). Sending the herd off the cliff edge: the disturbing interaction between herding and market-sensitive risk management practices. *Journal of Risk Finance*, 2(1):59–65.

Rubbaniy, G., van Lelyveld, I., and Verschoor, W. F. C. (2014). Home bias and dutch pension funds' investment behavior. *The European Journal of Finance*, 20(11):978–993.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *American Economic Review*, 80(3):465–479.

Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157):1124–1131.

Viet, D., Tan, G., and Westerholm, P. (2008). Correlated trading in concentrated market. *Journal of International Finance and Economics*, 8(4):148–163.

Voronkova, S. and Bohl, M. T. (2005). Institutional traders' behavior in an emerging stock market: Empirical evidence on polish pension fund investors. *Journal of Business Finance & Accounting*, 32(7):1537–1560.

Walter, A. and Moritz Weber, F. (2006). Herding in the german mutual fund industry. *European Financial Management*, 12(3):375–406.

Welch, I. (1992). Sequential sales, learning, and cascades. *Journal of Finance*, 47(2):695–732.

Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *Journal of Finance*, 54(2):581–622.

Wylie, S. (2005). Fund manager herding: A test of the accuracy of empirical results using u.k. data. *Journal of Business*, 78(1):381–403.

Table 2.1: **Descriptive Statistics of Trades Executed by Trade Leaders During 2013.** The following table shows descriptive statistics of all trades executed by trade leaders during 2013. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average number of lots a trader holds. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	2,640,972				
Number of Users	=	77,476				
Financial Instruments				**Trade Close Type**		
Currencies	=	83.14%		*Manual*	=	62.76%
Commodities	=	11.21%		*Stop Loss*	=	22.04%
Indicies	=	3.60%		*Take Profit*	=	13.14%
Stocks	=	2.05%		*Rollover*	=	2.06%

	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	66.11%	175	6.08	34.18	1	3.61
Min	0.0%	1.0	0	1	0.02	1
Max	100%	400.0	347	14,672	282	71
St.Dev.	0.355	156.51	17.24	166.32	3.20	4.36

Table 2.2: **Herding and Trading Intensity.** The top part of the table presents the herding measures $HLSV$ and $HFHW$ for the eToro data based on several minimum thresholds for the number of transactions executed. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), and monthly (M) subgroups; moreover, the relative bias, number of instrument-periods and average number of trades per instrument are also reported. The bottom part of the table presents means of the estimated herding measures, the relative bias, number of instrument-periods and average number of trades per instrument. In addition, the standard deviation (SD) and relative standard deviation (Rel. SD) to the mean of the herding measures are also reported.

Min. Trades	$HLSV$		$HFHW$		$\frac{HFHW-HLSV}{HFHW}$		Instrument-periods		Avg. num. of trades	
	Q	M	Q	M	Q	M	Q	M	Q	M
$n \geq 0$	0.169	0.165	0.232	0.239	27%	31%	317	847	12,911	4,502
	(0.007)	(0.005)	(0.003)	(0.003)						
$n \geq 100$	0.161	0.141	0.213	0.192	25%	27%	166	360	17,881	7,510
	(0.015)	(0.012)	(0.004)	(0.005)						
$n \geq 200$	0.144	0.138	0.193	0.188	25%	27%	132	332	21,100	7,964
	(0.019)	(0.011)	(0.007)	(0.005)						
$n \geq 300$	0.144	0.137	0.193	0.187	26%	27%	124	318	21,917	8,279
	(0.018)	(0.011)	(0.006)	(0.005)						
$n \geq 400$	0.139	0.138	0.187	0.189	26%	26%	115	313	23,185	8,375
	(0.023)	(0.011)	(0.008)	(0.005)						
$n \geq 500$	0.138	0.138	0.187	0.188	26%	26%	111	309	23,743	8,462
	(0.022)	(0.011)	(0.008)	(0.005)						
Mean	0.149	0.143	0.201	0.197	26%	27%	161	413	20,123	7,515
SD	0.013	0.011	0.018	0.021						
Rel. SD	0.086	0.077	0.090	0.104						

Table 2.3: **Herding and Leverage.** The top part of the table presents the herding measures $HLSV$ and $HFHW$ for the eToro data based on the different levels of leverage used. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), and monthly (M) subgroups; moreover, the relative bias, number of instrument-periods and average number of trades per instrument are also reported. The bottom part of the table presents means of the estimated herding measures, the relative bias, number of instrument-periods and average number of trades per instrument. In addition, the standard deviation (SD) and relative standard deviation (Rel. SD) to the mean of the herding measures are also reported.

Leverage	$HLSV$		$HFHW$		$\frac{HFHW-HLSV}{HFHW}$		Instrument-periods		Avg. num. of trades	
	Q	M	Q	M	Q	M	Q	M	Q	M
1	0.0	0.0	0.0	0.0	N/A	N/A	212	537	216	79
	(0.0)	(0.0)	(0.0)	(0.0)						
2	0.075	0.045	0.280	0.234	73%	81%	37	59	13	7
	(0.019)	(0.018)	(0.035)	(0.027)						
5	0.095	0.091	0.238	0.283	60%	68%	80	172	34	16
	(0.022)	(0.012)	(0.021)	(0.016)						
10	0.125	0.110	0.238	0.256	48%	57%	100	286	265	92
	(0.014)	(0.011)	(0.010)	(0.012)						
25	0.143	0.133	0.210	0.215	32%	39%	105	310	1,742	591
	(0.007)	(0.007)	(0.004)	(0.003)						
50	0.124	0.121	0.173	0.180	29%	33%	105	310	4,294	1,463
	(0.011)	(0.007)	(0.003)	(0.002)						
100	0.101	0.105	0.142	0.151	29%	31%	105	310	9,360	3,161
	(0.011)	(0.004)	(0.003)	(0.001)						
200	0.082	0.084	0.130	0.142	37%	41%	65	194	3,680	1,233
	(0.012)	(0.007)	(0.004)	(0.002)						
400	0.080	0.087	0.125	0.133	36%	35%	61	182	11,427	3,831
	(0.011)	(0.006)	(0.003)	(0.002)						
Mean	0.092	0.086	0.171	0.177	43%	48%	97	262	3,448	1,164
SD	0.042	0.041	0.084	0.085						
Rel. SD	0.453	0.476	0.491	0.478						

Table 2.4: **Herding and Trade Size.** The top part of the table presents the herding measures $HLSV$ and $HFHW$ for the eToro data based on trade size that are allocated to quintiles. Quintile 1 contains the largest trades while quintile 5 contains the smallest trades. Standard errors for each herding measure are shown in parentheses underneath the estimates. Herding measures are reported for quarterly (Q), and monthly (M) subgroups; moreover, the relative bias, number of instrument-periods and average number of trades per instrument are also reported. The bottom part of the table presents means of the estimated herding measures, the relative bias, number of instrument-periods and average number of trades per instrument. In addition, the standard deviation (SD) and relative standard deviation (Rel. SD) to the mean of the herding measures are also reported.

Trade Size Quintile	$HLSV$		$HFHW$		$\frac{HFHW-HLSV}{HFHW}$		Instrument-periods		Avg. num. of trades	
	Q	M	Q	M	Q	M	Q	M	Q	M
1 (Largest Trades)	0.188	0.168	0.318	0.303	41%	45%	246	569	2,613	991
	(0.024)	(0.013)	(0.024)	(0.013)						
2	0.166	0.161	0.260	0.272	36%	41%	284	653	2,171	811
	(0.017)	(0.010)	(0.017)	(0.009)						
3	0.154	0.139	0.255	0.242	40%	42%	255	585	2,821	1,041
	(0.021)	(0.009)	(0.018)	(0.009)						
4	0.123	0.117	0.180	0.185	32%	39%	267	666	3,377	1,231
	(0.011)	(0.007)	(0.007)	(0.005)						
5 (Smallest Trades)	0.169	0.150	0.269	0.254	35%	41%	266	649	5,906	2,095
	(0.030)	(0.013)	(0.019)	(0.010)						
Mean	0.160	0.147	0.256	0.251	37%	42%	264	624	3,378	1,234
SD	0.024	0.020	0.050	0.044						
Rel. SD	0.150	0.136	0.193	0.173						

Table 2.5: **Mean Contemporaneous and Time-Series Correlation of Purchase Intensities by Trade Leaders.** The table below presents the mean contemporaneous correlation in percent across groups in the first row. The other rows show the mean temporal correlations in percent from one to 11 months. The correlation between the two randomly selected groups of trade leaders represents the temporal correlation of purchase intensities by group one in month t with the purchase intensities by group two in month $t + \tau$, where $\tau = 0 \rightarrow 11$. The t-statistics are calculated based on the mean and standard deviation of the correlations. For $\tau = 11$ the t-statisitcs for the correlations of each group with itself cannot be computed due to the lack of degrees of freedom.

	Correlation of $\pi_{i,t}$ between Months t and $t + \tau$			t-statistics		
Horizon (τ)	$Group_1$ with $Group_1$	$Group_2$ with $Group_2$	$Group_1$ with $Group_2$	$Group_1$ with $Group_1$	$Group_2$ with $Group_2$	$Group_1$ with $Group_2$
0	100	100	98.5	NA	NA	282.3
1	93.0	91.3	91.9	58.8	44.0	76.7
2	90.7	89.8	89.9	39.8	37.5	54.7
3	84.8	83.6	84.1	36.4	32.9	48.1
4	80.7	81.4	80.9	25.8	28.9	37.7
5	79.1	78.2	78.7	26.2	26.3	36.7
6	79.1	81.1	80.0	20.7	25.5	33.8
7	77.3	77.5	77.1	17.1	24.0	29.6
8	77.5	79.8	78.3	23.5	26.4	33.5
9	75.3	76.8	75.9	36.3	29.3	34.6
10	71.3	75.9	73.0	75.8	15.1	29.0
11	68.9	71.6	69.9	NA	NA	37.8

Appendix A

HLSV Example

The following example demonstrates how to calculate the adjustment factor and the HLSV herding measure. Let the total number of traders active in security i during period t be $n_{i,t} = 5$, out of which the number of buyers is $b_{i,t} = 3$. Moreover, assume that the expected fraction of buyers $\hat{\pi}_t$ in period t is 0.55 (i.e. 55% of all transactions are buys). Given the HLSV measure presented below,

$$HLSV_{i,t} = |\pi_{i,t} - \hat{\pi}_t| - \underbrace{E\left[\left|\frac{\tilde{b}_{i,t}}{n_{i,t}} - \hat{\pi}_t\right|; \tilde{b}_{i,t} \sim B(\hat{\pi}_t, n_{i,t})\right]}_{AF_{i,t}}$$

calculating the left-hand term only without the adjustment factor would result in $|3/5 - 0.55| = 0.05$; however, this is not the true degree of herding since the real proportion of buyers cannot be 0.55 if there are five active traders. As such, the HLSV result should be adjusted for security i during period t by subtracting the expected outcome of $|\pi_{i,t} - \hat{\pi}_t|$ considering only five traders are active in the stock.

The expected outcome of $|\pi_{i,t} - \hat{\pi}_t|$ is the sum of all possible outcomes, multiplied by their probability of occurring. The probability is given by,

$$P(B = b) = \binom{n}{b} (\hat{\pi}_t)^b \times (1 - \hat{\pi}_t)^{n-b}$$

where n is the total number of active traders, b is the number of buyers, and $\hat{\pi}$ is the expected proportion of buyers. The table below shows the calculations for $E[|\pi_{i,t} - \hat{\pi}_t|]$.

$B_{i,t} = b$	$P(B = b)$	$\pi_{i,t}$	$\hat{\pi}_t$	$\|\pi_{i,t} - \hat{\pi}_t\|$
0	0.01845	0	0.55	0.01015
1	0.11277	0.2	0.55	0.03947
2	0.27565	0.4	0.55	0.04135
3	0.33691	0.6	0.55	0.01685
4	0.20589	0.8	0.55	0.05147
5	0.05033	1	0.55	0.02265
		$E[\|\pi_{i,t} - \hat{\pi}_t\|] =$		0.18194

Consequently, the $HLSV_{i,t}$ measure including the adjustment factor is $|3/5 - 0.55| - 0.18194 = -0.13193$. This number represents the proportion of traders on one side of the market above (or in this case below due to the negative sign) expectations given the expected fraction of buyers during that period. By ignoring the adjustment factor, the estimate for the level of herding would have been overstated.

Chapter 3

A Smart Man Learns from his Mistakes, A Wise Man Learns from the Mistakes of Others: Investigating the Disposition Effect of Trade Leaders on Social Trading Platforms

Abstract

There is ample evidence showing that traders can adjust for behavioural biases such as the disposition effect by learning from their past decisions. We investigate this hypothesis in the context of a social trading platform, which is governed by a scopic regime, and characterized by high information transparency regarding order flow and social interactions. We expect that traders in a scopic environment should exhibit weaker evidence of the disposition effect compared to traders in a traditional financial setting, since the former can learn not only from their own past trades, but also from the historical trades of all other participants disclosed by the platform. Using the disposition spread proposed by Odean (1998a), and the Cox proportional hazards model, we find ample evidence of a weaker disposition effect for traders in the scopic environment. Our results suggest that increased exposure to information allows traders to learn and adjust for the disposition effect more efficiently. This is opposite to what has been reported in an earlier study by Heimer (2015) who finds that heightened exposure to information leads to increases in the disposition effect.

3.1 Introduction

"Cut your losses" is a common saying that is told to encourage a person to stop wasting time or money on something that is seen as failing. Although this may seem as the logical path to follow, some individuals do not quite abide by this prescription. For instance, a well-known and distinctive phenomenon that has been investigated in behavioral finance is the tendency of investors to realize their gains and hold on to their losses. This behavior has been identified by Shefrin and Statman (1985) as the "disposition effect," which opposes rational economic models. Studies such as Odean (1998a), and Seru et al. (2010) have shown that investors who exhibit this bias tend to perform poorly. Nevertheless, many researchers have presented evidence that investors can learn from their past trading activity to decrease the disposition effect (Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Dhar and Zhu, 2006; Chen et al., 2007; Boolell-Gunesh et al., 2009; Seru et al., 2010). The reason, as financial economists advocate, is that more information allows investors to make better-informed investment decisions. Moreover, the efficient market hypothesis suggests that, as market information becomes more abundant and accessible, behavioral biases should cease to exist. Hence, given the findings in the literature, we argue that one should expect to find no (or weak) evidence of the disposition effect in an information-rich environment.

One such environment that has attracted an increasing number of retail traders is social trading, which embeds the traditional online trading model into a social media network. This novel concept is acclaimed for the high level of information transparency and disclosure that occurs in real-time, and the tools that are provided by these social trading platforms (STPs), which allow participants to interact with each other and even copy each other's trades using a mirror trading algorithm that is provided by the platform. We call this environment a "scopic regime" because it permits constant and reciprocal scrutiny of participants by the online community (Knorr Cetina, 2003). Participants on STPs can be divided into two main groups, which we label as trade leaders and investors (or copiers). The former are typically experienced traders who manage the funds allocated to them by the latter in return for monetary compensation that may be directly or indirectly based on performance (Doering et al., 2015). An investor can allocate his funds using the mirror trading algorithm, by easily and explicitly copying the future trades of another participant with a click of a button, thus receiving a price identical to that received by the copied participant. Nevertheless, our study focuses on the behavior of trade leaders, hence we define a trade leader as an individual who only manually enters trades into the STP. In other words, a trade leader is someone who executes original trades and refrains from explicitly copying others.

Given this definition, we use a unique data set from the highly popular eToro STP and we identify over 2.6 million trades executed by 77,476 trade leaders in 2013. We test whether exposure to a transparent and information-rich environment decreases the disposition effect. To do so, we adopt two methods: the first, proposed by Odean (1998a), calculates the disposition spread, and the second is based on the Cox proportional hazards model. Furthermore, we compare the results obtained for trade leaders on eToro to those of traders on a traditional online trading platform, which we call Anonymous, that does not offer integrated social networking features. We use overlapping periods and assets for the two data sets in order to examine whether the difference in disposition of traders between the two platforms is due to the characteristics of the trading environment.

In general, both empirical methods used show that trade leaders exhibit a weaker disposition effect compared to traders on the traditional trading platform, meaning that the high degree of information transparency and the abundance of financial as well as social information erode this behavioral bias, although not completely. On the one hand, this finding is in agreement with the efficient market hypothesis and the argument that, as information becomes more accessible, traders learn from these experiences in order to adjust for the disposition effect (Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Dhar and Zhu, 2006; Chen et al., 2007; Boolell-Gunesh et al., 2009; Seru et al., 2010). Another potential explanation for this finding is that the constant scrutiny by participants on STPs may drive trade leaders to close losing positions with almost the same propensity of closing winning positions, in order to avoid holding unjustifiable paper losses. On the other hand, our results oppose what has been reported by Heimer (2015), who examines a sample of retail traders on an STP, and finds that exposure to large amounts of information leads to significant increases in the disposition effect. The author argues that this relationship is driven by traders who strategically increase their search efforts for mutually beneficial peer-connections during times of prosperity. Hence, this conditional sharing of information and formation of connections naturally increases the disposition effect. Nevertheless, there are great differences between our data set and the one used by Heimer (2015). For instance, our sample only includes trade leaders who manually enter trades into the STP and avoid explicit copying, while Heimer (2015) uses all participants on the STP, and does not account for explicitly copied trades. This may bias the results in the direction of trade leaders with the most copiers. We discuss the latter study in more detail in section 3.3.2.

The remainder of this paper is organized as follows. Section 3.2 gives a detailed description of social trading platforms. Section 3.3 covers the theoretical and empirical literature on the disposition effect. Section 3.4 presents the two methods that are used in this study to estimate the disposition effect of trade leaders. The data sets from both eToro and Anonymous are presented in section 3.5, along with some statistics about the behavior characteristics of traders on the two platforms. Section 3.6 is dedicated to the discussion of the results. Finally, section 3.7 concludes the study.

3.2 Mechanics of STPs

STPs are founded on the notions of complete disclosure and free flow of information, thus allowing participants unlimited access to the profile information, current portfolio holdings and actual historical trading activity of traders. The high level of transparency on STPs, one that is not present in an institutional fund management setting, facilitates the constant scrutiny of past and current performance of traders. This unique feature differentiates STPs from traditional financial institutions, such as mutual funds and hedge funds, where performance is only disclosed quarterly by the former and voluntarily by the latter. Another key aspect that characterizes STPs is that they encourage cooperation between participants and facilitate discussions related to market research and trading strategies. This is because information sharing is incentivized through compensation schemes where trade leaders can earn monetary benefits for managing their investors' wealth.

In general, participants open an account on an STP that is directly linked to a brokerage account, or they can link their existing brokerage account to an STP, such as the platform used in the study by Heimer (2015). Next, they begin by posting their personal information on their profile page, which is publicly disclosed.

Whenever participants execute a trade on an STP, they transmit a trade signal, which can be defined as a set of rules to buy or sell a certain asset once the price reaches a predetermined level (Doering et al., 2015). We define a trade leader as an individual who only executes manual trades and refrains from explicitly copying the trades of others using the mirror trading algorithm provided by the platform. This group typically includes experienced traders who aspire to become leaders by building their reputation and displaying their skills through the trades they place. Trade leaders usually research and implement original trading strategies using their own capital; however, some STPs such as Ayondo allow individuals to become trade leaders by trading virtual money. Most STPs allow trades to be automatically executed by an automated trading algorithm if specific criteria are met. Hence, trade leaders typically aim to identify trades that are likely to yield significant profits in order to develop their track record, which is published on their profile page in real-time. Moreover, trade leaders are unrestricted in their competition to appeal to potential investors, which may be done by executing original manual trades, since such trades are an indication of a trader's knowledge, skills, and confidence.

Conversely, investors or copiers are less experienced traders who wish to have their capital managed by more experienced traders. They begin by conducting due diligence in order to evaluate the performance of trade leaders, and identify those who adopt a trading strategy that best suits their own investment goals and restrictions. Any additional information that investors may wish to attain in order to reduce uncertainty concerning the authenticity of the trade leaders may be collected via direct contact with the latter through instant messaging tools and discussion posts. This can result in a close, personal, and informal relationship between the parties involved. After investors evaluate the profile and performance of the different trade leaders, they can then set up their accounts to automatically copy the trades of specific trade leaders in real-time using the mirror trading algorithm offered by the STP. In other words, trades executed by the trade leader are instantaneously executed in the investor's account at a price identical to that received by the trade leader, without the need for manual confirmation. Unless the investor chooses to be involved in the daily investment process, it is unnecessary for him to interfere except for terminating the copying relationship. Conversely, if the investor chooses to remain involved in the investment process but is unable to organize his own thorough analyses, he may decide to copy only certain trades after evaluating the rationale behind them by clicking on the copy button pertaining to each trade.

Trading on STPs requires opening a position via a standardized Contract for Difference (CFD) that is written on an asset, since traders on STPs do not trade the actual asset. A CFD is an electronic contract between a trader and a CFD provider (or broker), which entails that the trader relinquish physical possession of the underlying asset for a contract with the CFD provider who offers an identical economic exposure (Norman, 2009). CFDs are considered derivative instruments that enable traders to obtain exposure to, and speculate about the direction of the asset, without ownership requirements. Such contracts allow the trader to take both long and short positions, where the payout is equivalent to the difference between the buy price of the underlying asset and the closing price of the contract. In general, a trader profits if he has a long (short) position in a CFD and the price of the underlying asset rises (falls). Moreover, the profits and losses of open positions are realized at the closing of the trading day and are then rolled-over to the next day, due to the fact that CFDs are settled daily. Furthermore, CFDs are traded on margin, thus the trader may deposit an amount of capital that is significantly smaller than the asset's notional value, which may lead to exceedingly leveraged positions. Traders must constantly maintain a sufficient amount of capital in their accounts in order to satisfy the minimum required margin established by the broker, otherwise the trader's positions may be liquidated.

3.3 Literature Review on the Disposition Effect

Many studies have provided evidence on the disposition effect, both theoretically and empirically. In general, the disposition effect has been found to have a negative impact on financial performance; however, several studies have shown that individuals can learn through experience to adjust for the disposition effect. We discuss the most relevant studies in the following sections.

3.3.1 Theoretical Studies

According to Shefrin and Statman (1985) the disposition effect can be attributed to an amalgamation of regret aversion, mental accounting, and problems with self-control, but with the fundamental explanation of this phenomenon being prospect theory as discussed by Kahneman and Tversky (1979). Unlike utility theory, prospect theory states that decision are made based on the potential values of gains and losses instead of the final outcome, and that the gains and losses are evaluated according to certain heuristics. For instance, gains and losses are typically compared to a certain reference point. As such, failing to acclimate to changes in price and relying on the original buying price as a benchmark would lead to referring to a rise in asset price as a sure gain if the asset is to be sold versus a risky decision if an investor is to hold on to it. The opposite is true for a decrease in asset price, where selling a stock would be considered as a sure loss, while holding on to it would be considered as an investor's affinity towards uncertainty and risk. This highlights the important role that an asset's purchase price plays in the disposition effect. Nevertheless, in reality, a certain reference point may develop via the combination of purchase, highest, and lowest prices since the investment date (Kahneman, 1992). Moreover, when the reference price and the current price are similar to each other, the degree of the disposition effect is reduced (Weber and Camerer, 1998).

Realizing gains and thus acquiring utility has been labeled as "realization utility" by Barberis and Xiong (2009, 2012), where the authors observe a disposition effect in circumstances where gains and losses are assessed at the time they are realized. Utility theory has been studied further by Frydman et al. (2014) who employ brain-imaging techniques to investigate buying and selling decisions, and found that when an individual sells a winner, he experiences a surge in utility. This brings forth the notion of emotions and how they may affect or even generate the disposition effect. For instance, Summers and Duxbury (2012) find that when experimental subjects do not actively decide on which stocks to add to their portfolios, no disposition effect is found. Furthermore, the authors find that if the subjects do not feel responsible for their choices, they cease to sell winning stocks more willingly than losing stocks. Accordingly, this implies that emotions such as regret and pride may play an integral role in behavioral patterns of the disposition effect. The emotion of regret has also been documented by Strahilevitz et al. (2011), who provide evidence that individual investors have a higher propensity of repurchasing an asset that they had already sold if the price has since decreased. The authors ascertain that such an action is due to the regret one endures when repurchasing at a higher price than what it is sold at, and to the rejoice one feels when repurchasing at a lower price. Further research has corroborated this aspect of emotion, where experiments have shown that participants demonstrate such a behavior solely when they are liable for the initial sale, signifying that investors attempt to avoid the feeling of regret resulting from the repurchasing of assets at prices higher than the original selling prices.

The relationship between the disposition effect and prospect theory has been challenged by several recent studies and the evidence has been mixed. For instance, Barberis and Xiong (2009) argue that prospect theory only explains disposition in some cases, while it predicts the opposite in other cases. Henderson (2012) show that investors have more affinity towards realizing gains than losses. Lehenkari (2012) studies the differences in the degree of disposition between investors who inherited stocks and those who purchased the stocks, and reports a higher disposition effect for the latter group of investors. From a different standpoint, other researches have found dissimilar results. For example, a preference for prospect theory may 1) result in holding on to both winning and losing investments (Kaustia, 2010), 2) may lead investors to cooperate with others who have constant relative risk aversion, thus usually leading to a negative-feedback trading tendency and encouraging both disposition effect and contrarian behavior (Yao and Li, 2013), and 3) may even drive investors not to purchase assets from the start (Hens and Vlcek, 2011).

Nevertheless, the dominant argument in the literature is that the effects of the reference point are "cognitive illusions" that cannot be easily removed; however, individuals can still attempt to understand them and aim to prevent such predispositions via a more systematic analysis of market conditions (Kahneman and Riepe, 1998). Consequently, Wegener and Petty (1995) suggest that correcting mechanisms may arise when one obtains a better understanding of circumstances. When an investor is conscious about his affinity towards holding on to a losing asset, he may be able to assess the outcomes of his decisions over time, thus giving rise to an alteration of his behavior. Researchers including Grinblatt and Keloharju (2001), Feng and Seasholes (2005), and Dhar and Zhu (2006) study whether an investor's prospects of learning is responsible for the difference in the willingness to keep losers, and find that an investor to whom information is available exhibits a much lower disposition effect compared to others. This brings forth the argument of whether an individual utilizes the experiences he gains in order to adjust for this behavioral bias. In other words, the influence of the disposition effect is assumed to be less evident with traders who are more experienced, since the acquired experience diminishes the effects of this behavioral bias. The existence of learning effects has been observed in experimental markets, where start-up and equilibrium behavior are shown to be dissimilar to each other (Knez et al., 1985). Moreover, Dhar and Zhu (2006) provide evidence showing that traders who operate more frequently are less likely to exhibit the disposition effect than those who do not trade as often, thus verifying that one can learn through experience to adjust for the disposition effect.

While the "learning through experience" argument has been verified by many studies, this paper takes a different approach and aims to investigate whether the amount and quality of information made available to individuals have a supplementary adjustment influence on the disposition effect. In particular, we argue that a transparent and information-rich environment such as a scopic regime, allows individuals to learn not only from their own experience, but also from the experiences of all other participants in order to adjust for the disposition effect.

3.3.2 Empirical Studies

Only one paper has empirically examined the disposition effect of traders on STPs, as such, we discuss this paper in detail in order to highlight some key differences compared to our study. Heimer (2015) uses data obtained from a STP, where retail traders can link their existing account at a foreign exchange brokerage to their social account on the STP. This allows the STP to access a trader's entire trading record, including transactions executed before the date of joining the STP. All new trades are entered through the retail brokerage platform, but are also recorded in the STP's database. This process differs compared to that adopted by the STP in this study, since eToro provides both the social as well as the brokerage services to the traders, hence there is no need for the trader to open an account with an independent broker. This also ensures homogeneity among traders in our sample in terms of services provided by the brokerage firm. The sample used by Heimer (2015) only includes participants who traded before and after joining the STP, resulting in around one million transactions executed by 2,598 participants from early 2009 until December 2010. It is critical to note two key differences between the data set used by the author and the one employed in this study. First, his study does not differentiate between traders who execute manual trades only and those who explicitly copy others, as we do in this study. This results in perfectly correlated transactions, which may lead to inaccurate statistical inferences. Second, the participants in the author's study are the same individuals who trade before and after joining the STP. As such, these individuals may learn from their past trades in order to correct for the disposition effect as argued in the literature. On the contrary, our study employs two data sets, each having its unique set of traders who trade in an overlapping period. With respect to the methodology, Heimer (2015) applies a discrete-time model, where the dependent variable is recorded at ten-minute intervals, and takes the value of one if the trader reduced his holdings in the asset and zero otherwise. We argue in section 3.4.2 that the time interval used is arbitrary and may lead to loss of information, especially since the transactions are time-stamped. Heimer (2015) finds that the disposition effect of traders prior to joining the social network is around 2.1%, and that this figure almost doubles to around 3.7% after joining the network, indicating that exposure to the social network increases the disposition effect. Moreover, the results are unaffected after the inclusion of trader fixed-effects. He also studies the relationship between the rate of issuing communication through the platform's messaging service and the disposition effect, and finds a negative relationship. Additionally, he also finds that the rate of receiving messages is independent of the disposition effect. Nevertheless, the key finding presented by the author is that increased access to social networks and information leads to large increases in the disposition effect.

Many studies have presented empirical evidence on the disposition effect in traditional financial environments. For instance, Odean (1998b) uses the trading records of 10,000 accounts at a large U.S. discount brokerage from 1987 to 1993, and observes that gains are 50% more likely to be realized relative to losses. This finding has also been corroborated by Weber and Camerer (1998) who find that, in an experimental stock market, winning stocks are 50% more likely to be sold relative to losing stocks. Moreover, the authors also discern that the requirement to sell and then repurchase all positions alleviates the disposition effect. Similar results have also been found in a sample of Finnish investors between the years 1995 and 1996, where the propensity to hold on to losers was also empirically documented (Grinblatt and Keloharju, 2001). Specifically, a stock that has experienced a capital loss of up to 30% is around 21% less likely to be sold compared to a stock that has increased in value, while a stock that has experienced more than a 30% capital loss is 32% less likely to be sold (Grinblatt and Keloharju, 2001). Similar results are also found using hazard rate models where Feng and Seasholes (2005) employ a sample of 1,511 Chinese investors in 2000, and show that these investors have a 32% less propensity of realizing a loss. Furthermore, Chen et al. (2007) examine the transactions of 50,000 investors at a Chinese brokerage firm between 1998 and 2002 and find a 67% higher chance of selling a winning asset than a losing one.

The substantial evidence on the disposition effect has motivated researchers to study the relationship between this bias and other individual characteristics, such as investor sophistication, experience, and the use of automated trading systems (Richards et al., 2015; Nolte, 2012; Boolell-Gunesh et al., 2009; Chen et al., 2007; Dhar and Zhu, 2006; Feng and Seasholes, 2005).

There is no consensus in the literature on how to define investor sophistication, which has resulted in the use of several proxies that differ greatly across studies. For instance, Shapira and Venezia (2001) use the professional occupation of an individual, Grinblatt and Keloharju (2001) and Brown et al. (2006) classify institutional investors as sophisticated, Seru et al. (2010), Chen et al. (2007), and Dhar and Zhu (2006) consider wealth and income, and Feng and Seasholes (2005) and Boolell-Gunesh et al. (2009) look at the degree of diversification of an individual's portfolio. Nevertheless, regardless of the measure used, the general findings show that the disposition effect decreases the higher the level of investor sophistication. For example, Grinblatt and Keloharju (2001) find a higher propensity of not selling losing investments among households, governmental and non-profit institutions, as well as non-financial corporations as compared to financial and insurance institutions. Feng and Seasholes (2005) show that the most sophisticated investors have a reduced sensitivity to selling losing investments of at least 67%. Dhar and Zhu (2006) also confirm that the disposition effect for individual investors is less pronounced for wealthy and professional traders. This finding is robust even after the authors account for potential confounding effects between income and occupation. A similar conclusion is also echoed in the work of Calvet et al. (2009) who use a sample of Swedish investors between 1999 and 2002, and find that households are more likely to fully sell stocks that have performed well. Furthermore, Barber et al. (2007) examine the disposition effect for several types of institutional investors (such as mutual funds, corporations, dealers, and foreigners) and find that this effect is more pronounced for individual investors. More specifically, they examine transaction records for investors in the Taiwan Stock Exchange between 1995 and 1999, and find that although both institutional as well as individual investors experience the disposition effect, the latter are four times more likely to sell a winning stock than a losing one. Furthermore, Nolte and Voev (2011) examine the relation between portfolio performance and the disposition effect for sophisticated investors as measured by trade size. The authors find that those who traded larger positions were more likely to close positions when the performance of the portfolio was positive, and that this behavior was absent among smaller investors. This is an indication that more sophisticated investors employ a broader portfolio investment strategy, while smaller, less sophisticated investors are more narrow-framed and less mindful of the dependencies between positions in their portfolio.

The disposition effect has also been found to be most prominent in financially inexperienced investors. For instance, Feng and Seasholes (2005) measure experience based on an individual's number of cumulative trades, and show that the disposition effect disintegrates as time passes after the first transaction. This is similar to the results obtained by Seru et al. (2010), who scrutinize transaction records for individual Finnish investors between 1995 and 2003, and observe that the disposition effect decreases with investor experience. It is important to note, however, that this effect is only found when trading experience is measured in number of transactions, but declines significantly when measured in years. Nevertheless, Chen et al. (2007) report that investors with more years of investment experience exhibit a lower disposition effect. Thus, it can be concluded that trading experience, wealth, as well as investor sophistication decrease the disposition effect. In other words, investors can learn through experience to avoid or adjust for the disposition effect.

Studies have also examined the association between automated trading systems and the disposition effect. Linnainmaa (2010) examines sell limit orders that were placed above the purchase price of the stock, and finds that such a trading strategy increased the disposition effect exhibited by investors. This result is intuitive since an increase in price would trigger the sell limit order, which would consequently turn paper gains into realized gains. Nolte (2012) investigates the effects of both take profit and stop loss limit orders on the disposition of traders in the foreign exchange market. Take profit orders are similar to sell limit orders, such that they increase the disposition effect, while stop loss orders are used to limit losses. The author argues that there exists an inverse disposition effect for trades with small profits and losses, and that this phenomenon is due to traders' use of stop loss and take profit strategies. A more recent study by Richards et al. (2015) uses trading records of individual investors in the U.K. from 2006 to 2009 and applies hazard models to investigate the effect of stop loss orders on the disposition effect. The authors show that traders who use stop loss orders have a higher conditional probability of selling stocks at a loss, relative to the baseline. Moreover, traders who use stop loss orders have a lower probability of realizing the gains of good performing stocks. These findings suggest that using stop loss orders decreases the disposition effect.

Investors' reluctance to realize losses is inconsistent with a tax-efficient strategy. Such a strategy would posit that one should ideally postpone realizing taxable gains by holding on to these winning investments, and realize losses in order to decrease tax liability. For instance, Constantinides (1984) demonstrates that when one takes into account transaction costs, and when there is no difference between long-term and short-term tax rates, investors should gradually increase their tax-loss selling from January to December. Barber and Odean (2004), examine the disposition effect of traders for taxable and tax-deferred accounts using two large data sets of individual traders from January 1998 to June 1999. The authors report that, for traders at both the discount and full-service brokers, the disposition effect is reversed in the month of December in taxable accounts, but not in tax-deferred ones. A similar study by Ivković et al. (2005) applies a Cox proportional hazards model to a data set obtained from a U.S. discount brokerage and finds evidence of a reverse disposition effect in taxable accounts, not only in December, but also throughout the year. These findings, along with many others (Feng and Seasholes, 2005), suggest that while taxes do influence the trading behavior of investors, they do not explain the disposition effect exhibited by individual traders.

Given the theoretical contributions and empirical evidence in the literature, we argue that the scopic regime governing STPs should induce a supplementary adjustment impact on the disposition effect, whereby trade leaders learn not only from their personal historical trading activity, but also from the trades of others. As such, we expect trade leaders on STPs to exhibit a weaker disposition effect compared to traders in an environment that does not offer as much information in terms of both quality and quantity.

3.4 Methodology

In this study, we employ two methods for estimating the disposition effect of trade leaders on STPs. The first was developed by Odean (1998a) to calculate the disposition spread, while the second method is based on the Cox proportional hazards model. We present these methods in the following sections.

3.4.1 Disposition Spread

To investigate whether the scopic regime decreases a trade leader's propensity to sell profitable trades and hold on to losing ones, we look at the frequency with which they realize gains and losses relative to their opportunities to close each of these positions. Following Odean (1998a), we calculate for each trade leader i, during the trading period t the realized gains RG_t^i, paper gains PG_t^i, realized losses RL_t^i, and paper losses PL_t^i in terms of number of trades as well as net dollar values. It is very important to note that most of the studies in the literature deal with institutional or individual investors who trade the actual asset, and who have long term investment horizons where they may hold an asset for a prolonged period without incurring any overnight fees. Moreover, the data employed by these studies show the quarterly holdings of these investors, thus the previously mentioned parameters are computed on a quarterly basis. In our study on the contrary, trade leaders on STPs trade assets through CFDs, thus they do not hold ownership of the assets and they incur overnight fees for positions held until the next trading day. Nevertheless, the high levels of leverage employed by trade leaders allow them to benefit from the slightest price swing, hence, these traders have a very short time horizon. Due to these reasons, calculating the above mentioned parameters based on a quarterly trading period would result in inappropriate estimates of the disposition effect since trade leaders are highly likely to close their positions within a few weeks or even days of opening them. To illustrate, consider a simple scenario with a single trader who buys two assets A and B on day one, and that both these assets appreciate over the next few days. Assume that the trader closes his position in asset A on day one, and his position in asset B on day two. If we consider a trading period of one day, we would obtain count values for RG and PG equal to one and one, respectively on day one, and values of one and zero, respectively on day two. Averaging across these two trading period would result in RG of one and PG of 0.5. Now, consider the scenario where the trading period is two days; thus, we would obtain count values for RG and PG of two and zero, respectively. As such, choosing a longer trading period in the context of short term trading would mean that most positions would have been closed, regardless of whether the trade was a win or a loss. This example clearly shows that the values computed for the realized and paper gains and losses are highly dependent on the trading period chosen. Due to this, we compute these parameters for different trading durations, $t = [1 \rightarrow 14]$ days.

Next, we aggregate the abovementioned parameters across all trade leaders, and over all trading periods, in order to calculate the proportion of gains realized (PGR) and the proportion of losses realized (PLR). The two ratios can be expressed as follows:

$$PGR = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\frac{RG_t^i}{RG_t^i + PG_t^i} \right) \qquad \text{and} \qquad PLR = \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\frac{RL_t^i}{RL_t^i + PL_t^i} \right). \quad (3.1)$$

The overall disposition spread, $DISP$, is calculated as the difference between the two proportions such that $DISP = PGR - PLR$, where a large positive (negative) spread means that trade leaders are more willing to realize gains (losses). The hypothesis to be tested is that trade leaders tend to close winning positions and hold on to losing ones, provided that one uses a reasonable trading period. The null and alternative hypotheses can be written in terms of proportions of realized gains and losses as:

$$H_0 : PGR \leq PLR \qquad \text{and} \qquad H_A : PGR > PLR,$$

where a one-tailed test can determine whether to reject the null hypothesis. Note that the test for significance in this case counts each realized gain, paper gain, realized loss, and paper loss as a separate independent observation, which are then aggregated across all traders.[1] This independence assumption will not hold perfectly in the context of social trading, since trade leaders have a tendency to herd and imitate each other's trading activities (Gemayel and Preda, 2015). As such, the

[1]The t-statistic is calculated as follows:

$$t - statistic = \frac{(PLR - PGR) - 0}{\sqrt{\frac{PGR(1-PGR)}{RG+PG} + \frac{PLR(1-PLR)}{RL+PL}}}$$

lack of independence will result in an inflated t-statistic; however, it does not bias the calculated proportions of realized gains and losses. Odean (1998a) argues that when the test statistic is large enough, as presented in our results, some lack of independence is not problematic. However, when t-statistics are close to the critical thresholds of statistical significance, one should analyze the results with caution. In aim of decreasing the likelihood of dependence among transactions, we propose using a very short trading period, which makes it less likely that trades within that short time frame are correlated. This argument is based on the findings of Gemayel and Preda (2015) who show that herding persists across time; hence, using a short trading period would decrease the degree of correlation among trades within that time frame. Choosing a short trading period would also allow us to adequately examine the disposition effect for short-term traders who would otherwise have all their positions closed if we compute the proportions of realized gains and losses using a long trading period.

Odean (1998a) proposes an alternative way of calculating the disposition spread by making different independence assumptions. Instead of assuming that independence exists at the trade level, we assume that it only exists at the trade leader level. This means that there may exist some form of relationship among the proportion of gains and losses realized within a trader's account but not across accounts. Again, this assumption may not hold entirely given the evidence on herding among traders in a scopic environment (Gemayel and Preda, 2015). The PGR and PLR variables are calculated for each trader during every trading period, and are then differenced to obtain the $DISP$ spread. We then average this spread for each trader across all trading periods in order to obtain a disposition spread for each trader separately. PGR and PLR for each trader-period can be calculated as:

$$PGR_t^i = \frac{RG_t^i}{RG_t^i + PG_t^i} \qquad \text{and} \qquad PLR_t^i = \frac{RL_t^i}{RL_t^i + PL_t^i}. \tag{3.2}$$

While the first method of calculating the proportions of gains and losses realized weights each trader by the number of realized and paper gains and losses, this alternative method weights each trader account equally. As such, the latter method ignores the fact that traders who are more active and execute more transactions result in more accurate estimates of their true PGR and PLR values. Going back to the subject of observation independence, choosing a short trading period may decrease the likelihood of having correlated trades within the same trading period; however, this manoeuvre in itself results in another issue. To elaborate, we draw on our finding that trade leaders on eToro and traders on Anonymous have weekly trading frequencies of 1 and 2.15, respectively. These figures amount to less than one trade a day. For the purpose of simplicity, assume a trading period of one day, where a trader opens and closes one trade within a trading day. Hence, that trader would have either a PGR equal to one and PLR equal to zero if the trade was a win, or a PGR equal to zero and PLR equal to one if the trade was a loss. In these two scenarios, the $DISP$ spread will take on the value of either 100% or -100%. As Odean (1998a) notes that the proportions of realized gains and losses will be smaller for traders who trade frequently compared to those who trade less frequently. Hence, given that traders in our two samples are not likely to have multiple trades opened at once, this results in extreme values for the $DISP$ spread, which may not reflect the true disposition effect of the trader. Moreover, as the values of the parameters used in calculating the $DISP$ spread will be relatively low, this will result in a very low test statistic.

Given that the two methods presented above for calculating the disposition spread vary greatly depending on the trading period used, and on the independence assumption made, one must analyze these results with caution. While the test statistics may be somewhat biased and not very reliable when they are close to the traditional critical values of significance, the estimated disposition spreads are not, and provide a sensible starting point to investigate disposition differentials between the two data sets.

Finally, Odean (1998a) highlights that, while the disposition spread is useful for assessing whether entities are more likely to realize gains than losses, this measure is not appropriate for cross-sectional comparisons. The reason is due to the mechanical relationship between the disposition spread and the size of the portfolio. To illustrate this point, we reproduce the example provided by Cici (2012). Assume that trader A has a portfolio consisting of 12 winners and 12 losers, while trader B has a portfolio with three winners and three losers. Moreover, let both traders be equally influenced by the disposition effect, such that they are both twice as likely to realize a gain relative to a loss. Therefore, both traders would sell two winning assets and one losing assets, resulting in PGR and PLR values of 2/12 and 1/12, respectively for trader A, and PGR and PLR values of 2/3 and 1/3, respectively for trader B. Based on these figures, this means that the $DISP$ spread of trader B is four times larger compared to that of trader A, despite both traders having the same propensity to realize winners relative to losers.

The disposition ratio, denoted by $DISP\ RATIO$ and calculated as the ratio of PGR to PLR, overcomes this issue by correctly estimating the disposition to sell winners compared to losers. In the previous example, both traders would have the same disposition ratio, hence we also present this measure in our analysis.

The disposition spread and ratio are good metrics to calculate the likelihood of realizing gains versus losses, especially for entities that have long term investment horizons such as investment funds. Nevertheless, several issues arise when applying these measures in the context of short term trading, as mentioned earlier. Hence, we also adopt a survival analysis approach to estimate the disposition effect while controlling for trader characteristics, and dependence among trades.

3.4.2 Cox Proportional Hazards Model

We apply survival analysis techniques to measure the duration until an event occurs, which in our case is the closing of a trade. This allows us to estimate regression models where the dependent variable is a measure of the rate of event occurrence. Hence, one must specify an "origin time" based on which the event time is measured, since the risk of the event varies as a function of time since that origin. While in many studies the origin time is ideally the same for all observations, our data includes many trades that are executed at different points in time. Fortunately, an important feature of survival analysis is that it can handle truncated data, for which there is a systematic exclusion of survival times from the sample, and where the sample itself is dependent on the survival time (Allison, 2010). One particular type is left truncation, which is also known as delayed or late entry into the sample. In our study, left truncation occurs because trades are executed at different points in time, thus entering the sample at delayed but known dates.

Many of the techniques used in survival analysis assume that time is measured as a continuous variable. While it may be true that events occur in continuous time, such an assumption may lead to computationally intensive processes. Hence, some researchers have proposed using discrete-time models, where events are recorded in grouped form and are considered to occur at discrete time points. In this case, even though the exact time of an event is known, one may choose to divide continuous time into small discrete time intervals and create a binary variable representing whether or not the event has taken place within that time interval. This method may be less computationally intense compared to continuous time models, and is not an unreasonable exploratory technique; however, it is far from ideal, especially when one already knows the exact dates of the event occurrences. In addition to the known limitations of employing a dummy dependent variable in a multivariate regression (Goldberger, 1964), dichotomizing data over discrete time intervals is highly arbitrary and wasteful of information (Allison, 1982). For instance, Heimer (2015) applies a discrete time method by transforming time-stamped transactions of traders on the STP into ten-minute intervals. This approach is arbitrary because the ten-minute interval does not hold any meaning, and it ignores the variation on either side of the interval cutoff point. For example, one might argue that a trader who closes his position one minute after the trade exhibits a gain has a higher propensity towards realizing gains relative to losses compared to a trader who closes his losing position after nine minutes. However, since both these trades are closed within the ten-minute interval in a discrete-time context, this method does not account for the variation that allows us to differentiate between the disposition to close a position contingent on being a gain or a loss. Thus, a critical issue to be considered is the length of the time interval used for grouping events relative to the typical rate of an event occurring. The smaller the ratio of the former to the latter, the more suitable it is to utilize a continuous-time specification (Allison, 1982; Jenkins, 2005).

In order to avoid such subjectivity in selecting an appropriate discrete time interval, and given that the transactions in our data sets are time-stamped, we use a continuous-time model.[2] In particular, we apply the Cox regression proposed in the seminal work of Cox (1972), which is one of the most widely used techniques for modeling hazard rates. This model is often referred to as semi-parametric since it does not make specific assumptions regarding the probability distribution of event occurrences, and it uses a partial-likelihood method of estimation.

[2]It is important to note that as the time interval becomes smaller, the discrete-time hazard rate gets closer to the continuous-time hazard rate, and the discrete-time survival function converges to the continuous-time one (Jenkins, 2005).

The general Cox model we estimate takes the following form:

$$\begin{aligned}\lambda(t, X_i) &= \lambda_0(t)e^{\beta' X_i} \\ &= \lambda_0(t)\lambda_i\end{aligned} \tag{3.3}$$

where, $\lambda(t, X_i)$ is the hazard rate at time t conditional on a set of observed predictor variables, X_i. The baseline hazard rate, $\lambda_0(t)$, is the hazard rate when all predictor variables are null. Since transactions executed by a trader may exhibit dependence, we incorporate into our framework unobserved individual heterogeneity. Given the set of i transactions that are executed by j independent individuals, we denote by b_j the random cluster effect that induces correlation among the transactions in the same cluster j, where we assume that the random effects $b_1, \ldots, b_j$ are i.i.d. random variables with $b_j \sim N(0, \sigma^2)$. Hence, observations from different clusters are independent; however, the dependence between observations within a cluster j is induced by b_j, such that the observations within cluster j are independent, conditional on b_j. Note that using random effects — especially in this study where we examine thousands of traders — can substantially decrease the number of estimated parameters compared to a fixed-effects model. The random-effects Cox model is expressed as:

$$\lambda_{ij}(t, X_{ij}, Z_{ij}) = \lambda_0(t)e^{\beta' X_{ij} + b_j' Z_{ij}} \tag{3.4}$$

where λ_0 is an unspecified baseline hazard function, which is the hazard rate when all covariates take on the value of zero. X and Z are the design matrices for the fixed-effects and random-effects, respectively, and β and b are the fixed-effects and random-effects coefficients, respectively. The hazard rate, $\lambda_{ij}(t, X_{ij}, Z_{ij})$, is the probability density function of the event occurrence at time t conditional on the survival to that time. Inference under the random-effects Cox regression is conducted using the full likelihood.

The survival time in our study is computed in seconds as the difference between the closing and opening time-stamps of each transaction. Moreover, all positions in both data sets have been closed, meaning that the hazard event has occurred for all observations. The predictor variables employed in the analysis include the following:

- *Gain*: a dichotomous variable to estimate the disposition effect, which takes the value of one if the transaction is a gain and zero if it is a loss;

- *Long*: a dichotomous variable that takes the value of one for a long position and zero for a short position;
- *Leverage*: a categorical variable that captures the degree of leverage used based on the leverage levels offered by the trading platforms[3];
- T/P: a dichotomous variable that takes the value of one if the position is closed due to a take profit order, and zero otherwise; and
- S/L: a dichotomous variable that takes the value of one if the trade is closed due to a stop loss order, and zero otherwise.

We conduct a series of interrelated regression models based on the Cox proportional hazards method discussed above on the two data sets. First, we fit an unadjusted model labeled Model (1), where we only use the *Gain* variable in order to investigate whether there is a difference in the magnitude of the disposition effect between the two trading environments. Next, we run an adjusted model, labeled Model (2), where we include the remaining control variables listed above. In this model, we allow for interaction between the variables, and we include asset fixed-effects. Finally, we fit a third model, labeled Model (3), that includes all variables from Model (2), in addition to trader random-effects. We conduct these analyses for each data set separately, and then repeat them for subsets that are selected by only considering the overlapping time frame and the common assets traded on the two platforms.

For all these models we report the coefficients, odds ratios (OR), and standard errors (S.E.) for all covariates. Moreover we report the concordance index, or Harrell's C, which is one of the most widely used performance metrics for survival models (Harrell, 2013). This measure is interpreted as the probability of concordance between the predicted and the actual survival times (Harrell et al., 1982).

3.5 Data

We make use of two data sets in order to compare the disposition effect of traders under a scopic and a traditional trading environment. We describe the characteristics of the two data sets in the sections below.

[3]The Anonymous platform offers only a leverage ratio of 200 to one, hence we do not include this variable when fitting the models to this data set.

3.5.1 Data from eToro

The first data set is obtained from the highly popular eToro STP, and contains over 63 million trades executed by all participants during 2013. Participants can trade in a wide range of assets including currencies, commodities, equities, and indices. Table 1.1 provides a list of the entire investment universe available to traders. The STP records the details of each transaction, including the opening and closing prices, amount traded, leverage used, direction, as well as the opening and closing time-stamps. Since we aim to study the disposition effect of traders who execute personal trades and refrain from explicitly copying others, we select trade leaders by applying a strict criterion where only participants whose trades were all entered manually into the platform during 2013 are included in our sample. Note that traders can execute a mix of manual and copied trades; however, we consider these individuals to be investors who allocate part of their capital to be managed by trade leaders, yet reserve a portion for personal trading.

The final sample contains over 2.6 million trades executed by 77,476 trade leaders. We present some descriptive statistics in Table 3.2. Trades can be categorized based on the asset traded as follows: currencies constitute 83.14% of trades, whereas commodities, equities, and indices make up 11.21%, 3.6% and 2.05%, respectively. Moreover, around 63% of these trades are personally closed by the traders, while 22% and 13% are triggered by stop-loss and take-profit orders, respectively. Next, we compute several behavioral trading characteristics, which are first averaged across trades of each trader and then across all trade leaders. On average, we find that trade leaders engage in both long (66.11%) and short positions, and employ a leverage ratio of 175 to one. These findings support the notion that trade leaders are considered to be sophisticated traders, since they take both long and short positions (Engelberg et al., 2012, 2014), and are confident enough in their trading skills to use high levels of leverage. With respect to the duration of trades, trade leaders keep positions open for an average of six days, which indicates that they are aware of the impact of rollover costs on profits associated with keeping positions open overnight. The average frequency of annual trades across trade leaders is around 34, which is considerably low compared to that of the full population of participants (207). This suggests that trade leaders are more aware of the impact of transaction costs on profits. Finally, we find that trade leaders are more specialized since they trade in a fewer number of assets (3.6 on average) compared to the full population of participants (6.5).

3.5.2 Data from Anonymous

The second data set is obtained from a foreign exchange broker, which we call Anonymous, and contains over 6.9 million trades in 22 currency pairs, executed by 22,545 traders over the period January 2011 to September 2013. Anonymous does not offer participants any social trading features such as mirror trading, thus we consider all trades to be unique. The list of currency pairs offered by Anonymous is presented in Table 3.1. Around 66.48% of trades are personally closed by the trader while 14.41% and 19.11% of trades are closed due to stop-loss and take-profit orders, respectively. Moreover, we calculate several trader behavior characteristics, which are first averaged across trades of each trader, and then across all traders. We present these statistics in Table 3.3. On average, we find that 47% of a trader's positions on the Anonymous platform are buys, which is around 20% less compared to trade leaders on eToro. This suggests that traders on Anonymous are more comfortable with riskier short selling strategies. Regarding trade duration, we find that the average trade on Anonymous is around 1.19 days, which is considerably less than the duration of trades on eToro. This means that most traders on Anonymous are day traders who close their positions at the end of the trading day. As such, they tend to minimize their exposure to overnight fluctuations in prices. With respect to the average number of annual trades, we report a figure of around 111 trades, which is almost three times the value reported for trade leaders from eToro. Given that traders on Anonymous are day traders, the higher trade frequency indicates that these traders seek to exploit intraday price swings. Finally, we find that traders on Anonymous trade in an average of 5.7 different currency pairs. While this number is low, indicating that these traders specialize in a few currencies, this figure is slightly higher than that of trade leaders, meaning that traders on Anonymous have a wider scope when searching for trading opportunities to exploit.

3.6 Results

In what follows, we present the results obtained from the two methods discussed previously for each of the data sets.

3.6.1 Disposition Spread Results

3.6.1.1 No Trader Clustering

We begin by calculating the disposition spread, $DISP$, by aggregating the realized gains, paper gains, realized losses, and paper losses on the basis of both trade counts and dollar values across all transactions and traders, before calculating the proportions of gains and losses realized. This analysis is repeated by varying the trading duration, $t = [1 \rightarrow 14]$, and the results are presented in the four panels of Table 3.4. We first conduct the analysis using all the observations in both data sets. Panel A shows that trade leaders on eToro exhibit a positive and significant disposition spread irrespective of the trading period or the basis used to calculate the parameters. This means that across all assets traded in 2013, trade leaders close a greater proportion of their winning positions than of their losing ones. Given the high t-statistics across all trading periods, we reject the null hypothesis that $PGR \leq PLR$. The average $DISP$ spread, PGR, PLR, and $DISP\ RATIO$ across all trading periods are 11.41%, 84.4%, 72.98%, and 1.22, respectively, when parameters are calculated based on trade count, and 11.62%, 45.11%, 33.49%, and 1.49, respectively, when parameters are based on trade dollar values. The disposition ratios indicate that positions exhibiting gains are between 22% and 49% more likely to be closed from one day to the next compared to positions that are losing. We also point out that as the trading period increases, both the PGR and PLR approach 100%, and the $DISP\ RATIO$ converges to one. This is expected in the context of short term trading since all positions, regardless of profitability, will be closed when considering a long trading period.

Regarding traders on Anonymous, the results presented in Panel B of Table 3.4 show that, over the period January 2011 to September 2013, traders exhibited positive and significant disposition spreads, which are also considerably greater than those reported for trade leaders on eToro across all trading periods considered. The average $DISP$ spread, PGR, PLR, and $DISP\ RATIO$ across all trading periods are 16.24%, 87.01%, 70.78%, and 1.38, respectively, when using trade counts, and 27.05%, 78.44%, 51.39%, and 3.72, respectively, when using dollar values. These values clearly show that traders on Anonymous exhibit a greater disposition effect compared to trade leaders on eToro.

In order to conduct a more comparable analysis, we recalculate the disposition spread parameters using an overlapping time frame between the two data sets, from January 2013 to September 2013. Additionally, we only consider the common subset of the assets traded on the two platforms, which includes 16 currency pairs. The results for eToro and Anonymous are presented in Panel C and Panel D, respectively, in Table 3.4. We find that trade leaders exhibit a significant disposition effect, with an average $DISP$ spread across all trading periods of 8.63% and 13.63%, depending on the basis used. With respect to traders on Anonymous, the mean disposition spreads are 21.64% and 34.92%, which are almost three times larger than the figures reported for trade leaders on eToro. The disposition ratios corroborate our results, showing that trade leaders on eToro have an average $DISP\ RATIO$ between 1.16 and 1.54, while traders on Anonymous have a ratio between 1.52 and 2.59.

All our findings show that, while both trade leaders on eToro and traders on Anonymous exhibit the disposition effect, this bias is much more pronounced among the latter. To summarize, the disposition ratios imply that trade leaders are between 16% and 54% more likely to close a winning position relative to a losing one, while traders on Anonymous are between 52% and 159% more likely to do so.

3.6.1.2 With Trader Clustering

We re-examine the disposition effect in the two data sets; however, we calculate the disposition spread and disposition ratio for each trader and then average them to obtain overall mean measures for each trading period. This allows us to account for potential dependence between trades executed by a certain trader. The results are presented in four panels in Table 3.5. Panel A shows the results for trade leaders on eToro throughout 2013 and including all assets offered by the platform. While the PGR and PLR ratios are still high (between 47% and 53%), these figures are closer to each other resulting in narrow disposition spreads across all trading periods, and even in negative spreads when t is large. Moreover, all estimates are statistically insignificant as indicated by the low t-statistics. While this method aims to account for potential dependence among trades executed by a certain trader, it also results in low parameter values. For instance, the top part of Panel A in Table 3.5 shows that the trade count of realized gains, realized losses, paper gains, and paper losses for $t \leq 6$ days are very small, which would result in an insignificant t-statistic. This is due to the fact that trade leaders on average have around one position open in a given week (see Table 2.1). As such, these results should be analyzed with caution.

Regarding traders on Anonymous (Panel B), we find that the disposition spread is statistically insignificant when using trade count as the basis for calculating the gains and losses, but it is significant across all trading periods when using trade dollar values. This inconsistency may be attributed to the issue mentioned earlier, where the trade count parameters are very small such that they result in insignificant test statistics. Nevertheless, the mean $DISP$ spread based on trade dollar values is found to be equal to 15.15%, which is almost half the value obtained in the initial analysis where dependency among trades was not taken into account. These results indicate that the disposition effect is only present in the traditional trading environment and not in the scopic regime.

For a more comparable analysis between the two trading environments, we re-estimate the disposition spreads and ratios using an overlapping time-frame, from January 2013 to September 2013, and we only consider the common subset of the assets traded, as we did earlier. The results for eToro and Anonymous are presented in Panel C and Panel D, respectively, in Table 3.5. For trade leaders on eToro, the $DISP$ spread remains largely insignificant, except for the few cases under the trade dollar value basis when the trading period $t \geq 12$. The t-statistics turn significant, yet remain close to the critical significance levels. Again, this significance should be taken with a grain of salt.

Finally, with respect to traders on Anonymous in the common sub-sample, we find statistically insignificant disposition spreads when using the trade count basis, but we report significant estimates across all trading periods under the trade dollar value basis. In particular, the mean $DISP$ spread is equal to 16.82% and the mean $DISP\ RATIO$ remains relatively high at around 37.

We summarize our results as follows. First, we find that when dependencies among trades executed by the same trader are not accounted for, traders under both scopic and traditional environments exhibit the disposition effect. However, the disposition effect under the former regime is considerably lower compared to traders in a traditional environment. Second, when dependencies among transactions are taken into account, the disposition effect of trade leaders on the STP becomes statistically insignificant, while the disposition effect of traders on Anonymous is only significant when using the trade dollar value basis, and is around half the estimate obtained when we do not cluster trades. While we recommend caution when analyzing these results — due to the low trading frequency in the short trading periods — one may conclude that the scopic environment governing STPs erodes the disposition effect as traders adjust for this bias by learning not only from their own past trades, but also from the trades of all other traders on the platform. Another potential explanation is that the constant scrutiny by investors on STPs prompts trade leaders to close losing positions with the same propensity of closing winning positions, in order to avoid holding unjustifiable paper losses.

3.6.2 Cox Regression Results

We conduct a series of Cox regression models on the entire data sets, and on comparable subsets. Since we obtain very similar results for each full data set and its subset, we only report and discuss the results for the common subsets in the sections below to avoid repetition.

3.6.2.1 eToro Common Subset

We fit the Cox regression models using the subsets of the two data sets with an overlapping time frame, from January 2013 to September 2013, and we only consider the common assets offered by the two platforms. The results for eToro and Anonymous are presented in Panel A and Panel B, respectively, in Table 3.6.

Starting with eToro, Model (1) shows that the *Gain* variable is significant and has a small negative effect on the hazard rate of trades, with an estimate of -0.042. This means that losses are more likely to be realized relative to gains. The concordance index for Model (1) is 50.5% , indicating that the model correctly predicts the survival of trades half of the time. This suggests that Model (1) can be improved by including other factors that could explain the hazard rate of trades. Next, we fit Model (2) and find that the effect of the *Gain* variable turns positive, but remains small with an estimate of 0.021, which suggests that trade leaders are 2.1% more likely to close a winning position relative to a losing one. We also find that long positions are around 6.8% more likely to be closed compared to short positions, as indicated by the coefficient of the *Long* variable.

Regarding limit orders, we report a negative relationship between the take profit, T/P variable and the hazard rate, with an estimate of around -1.255. The relationship persists even after accounting for the interaction between T/P and *Gain*. This may seem counter-intuitive at first in the sense that one would expect take profit orders to increase the hazard ratio, as profitable positions are closed once the market price reaches the take profit price. However, the T/P estimate is the effect of take profit orders on the hazard rate relative to trades that are personally closed by the trade leader. One explanation for this result is that trade leaders place wide take profit limits, which would require a longer trade duration for the market price to trigger the order. As for stop loss orders, we find that the S/L variable also has a negative effect on the hazard rate with a coefficient of -0.443, even after taking into account potential interaction with the *Gain* variable. Again, this can be explained by the wide stop loss limits used by trade leaders, which would require a longer duration for the price to reach the stop loss level. We argue that the wide take profit and stop loss levels are a strategic signaling mechanism employed by trade leaders, where they forgo realizing small profits in hopes of winning big, which would be perceived as a more attractive achievement by potential investors. Such a strategy can be implemented by placing wider take profit levels, and allowing for some flexibility for adverse price swings by placing a wider stop loss limit. In support of our argument, we find that trade leaders who use take profit and stop loss orders on eToro have average dollar gains and losses of 30.44 and -65.88, respectively, while those on Anonymous show average gains and losses of 24.56 and -56.1, respectively. These statistics show that trade leaders on eToro place wider take profit and stop loss limits. Finally, with respect to leverage, we report that the low leverage ratios of 5 to 1 and 10 to 1 have negative effects on the hazard rate, while ratios over 50 to 1 have a positive impact. These results are as one would expect since high leverage ratios translate into large price swings relative to low leverage ratios, which would accelerate trading activity by allowing trade leaders to realize sizable gains (or losses) within a shorter period of time. Moreover, the effect of leverage on the hazard rate as we move from a ratio of 50 to 1, to a ratio of 400 to 1 increases exponentially. This finding emphasizes the accelerated hazard impact that high leverage ratios have on trades. The concordance index of Model (2) is equal to 72.9%, which indicates that the control variables significantly improve the predictive power of the model.

Finally, in Model (3), we include trader random effects in order to capture heterogeneity among trade leaders and dependence among transactions executed by each trade leader. Interestingly, the coefficient for the *Gain* variable increases significantly to 0.27, meaning that trade leaders are 27% more likely to realize a gain relative to a loss. This result means that trade leaders exhibit the disposition effect, which is opposite to what we found when we used the method proposed by Odean (1998a). Specifically, when we accounted for potential dependence among trades, the disposition spread decreased and turned insignificant. Given the drawbacks discussed earlier about calculating the disposition spread in the context of short term trading, we argue that the Cox proportional hazards method is a superior alternative since it does not depend on an arbitrary trading time frame. With respect to the control variables, almost all coefficients decrease slightly yet remain statistically significant. One exception is that the leverage ratio of 10 to 1 became insignificant, while the ratio of 25 to 1, which was previously insignificant, became positive and significant. Nevertheless, this does not change the overall exponential relationship between leverage and the hazard rate. As for the concordance index, we report a value of 82.7%, which means that adding trader random effects increases the predictive power of the model.

3.6.2.2 Anonymous Common Subset

For traders on Anonymous, the results of Model (1) show that the *Gain* estimate is statistically significant and equal to 0.433, meaning that a winning position has a higher hazard rate relative to a losing position. The odds ratio indicates that traders on Anonymous are 1.75 times more likely to close a winning position compared to a losing one, and this figure is much higher compared to the result obtained for trade leaders on eToro (OR = 0.959). The concordance index of the model is 55.1%. The results for Model (2) show that, after including the control variables, the estimate of the *Gain* variable rises to around 0.7, which translates into a relatively high odds ratio of around two, compared to that of trade leaders (OR = 1.09). This clearly illustrates that traders on Anonymous exhibit a much larger disposition effect compared to trade leaders on eToro. Regarding the *Long* variable, we report a negative estimate of -0.054, meaning that long positions on Anonymous are closed at a slower rate relative to short positions, which is opposite to what we found for trade leaders on eToro. With respect to limit orders, we find that take profit orders have a positive impact on the hazard rate with a T/P coefficient of 0.59 (OR = 1.8). This means that take profit orders are 1.8 times more likely to be closed relative to manual orders, which is in line with our earlier argument that traders on Anonymous use tight take profit limits. Hence, it is very probable that the market price will trigger the take profit order and close the trade. This is especially probable since the Anonymous platform imposes a leverage ratio of 200 to 1, which magnifies the price swings and increases the likelihood of the limit order being triggered. Similarly for stop loss orders, the impact on the hazard rate is also positive with a S/L coefficient of 1.28 (OR = 3.6). This finding is in agreement with the fact that these traders use tight stop loss orders, resulting in a high probability that even small price swings will trigger these orders within a very short duration. Since the Anonymous platform applies a 200 to 1 leverage ratio to all trades, it is not possible to estimate the effect of the variation in leverage on the hazard rate. The concordance index of Model (2) is equal to 63.1%, which is an improvement over the predictive power of Model (1).

Finally, Model (3) includes trader random-effects, which increase the coefficient of the *Gain* variable to 0.9 (OR = 2.46). This is around three times greater than the estimate obtained for trade leaders on eToro for the same model. As such, we can conclude that, all else equal, the disposition effect exhibited by traders in a traditional trading environment is considerably larger than that exhibited by traders in a scopic environment. In other words, the scopic regime erodes the disposition effect of traders, although not entirely. With respect to the *Long* variable, the coefficient turns positive and significant, but remains very small, 0.006. The coefficients for T/P and S/L decrease to around 0.14 and 1.04, respectively, yet remain significant. As for the concordance index, we report a high value of 82.3%.

3.7 Conclusion

In this paper, we examine the disposition effect of traders in a scopic and a traditional trading environment in order to test whether high levels of transparency and the free flow of information decrease this behavioral bias. We build on the existing literature and argue that traders can learn to adjust for the disposition effect more efficiently when they have access to aggregate information on order flow, as compared to learning only from their own experience. To study this, we use a data set from the highly popular eToro STP containing over 2.6 million transactions executed by 77,476 trade leaders, and another data set from a traditional trading platform called Anonymous, which contains over 6.9 million transactions executed by 22,545 traders. We apply two empirical methods that are used in the literature. Using the measure proposed by Odean (1998a), we first calculate the disposition spread without accounting for dependence among trades and find that, while traders on both platforms exhibit the disposition effect, traders in the scopic environment show a lower bias. When we cluster the trades by trader, we only find evidence of the disposition effect for traders on Anonymous.

The second empirical method employs a series of Cox proportional hazards models, where we find evidence of the disposition effect for traders in both trading environments. Moreover, we find that the disposition effect of traders in the traditional financial environment was around three times larger compared to that of traders in the scopic environment when we included trader random-effects.

While there are some absolute differences in the results generated by the two methods, the overall relative conclusion is the same. Specifically, we find ample evidence showing a weaker disposition effect for traders in a scopic environment compared to traders in a traditional trading setting. This finding is consistent with the learning hypothesis discussed in the literature, where trade leaders on STPs can adjust for this behavioral bias by learning not only from their own historical trades, but also from the trades of others. As transactions are published by the STP in real-time, trade leaders can learn to avoid realizing gains prematurely, and understand how realizing losses is consistent with a tax-efficient strategy. Nevertheless, this does not suggest that traders in a traditional financial setting do not learn from their own historical trades. We argue that traders in a scopic environment learn at a faster rate compared to traders in a traditional trading setting. However, more work is required to test this proposition, and the argument of whether the scopic trading environment erodes the disposition effect completely is still debatable and requires further research.

Academics such as Dhar and Zhu (2006) propose that brokerage firms should educate their clients about behavioral biases that may adversely impact their performance. While this approach would surely make individuals more aware of the factors that influence their trading activity, we show that by simply increasing information transparency, individuals can very efficiently learn on their own to avoid the disposition effect by observing the actions of others. This phenomenon is a manifestation of how efficient markets are self-regulating, as heightened exposure to information erodes behavioral biases, which would in turn lead to improved price discovery.

Bibliography

Allison, P. D. (1982). Discrete-time methods for the analysis of event histories. *Sociological Methodology*, 13(1):61–98.

Allison, P. D. (2010). *Survival analysis using SAS: a practical guide*. Sas Institute.

Barber, B. M., Lee, Y.-T., Liu, Y.-J., and Odean, T. (2007). Is the aggregate investor reluctant to realise losses? evidence from taiwan. *European Financial Management*, 13(3):423–447.

Barber, B. M. and Odean, T. (2004). Are individual investors tax savvy? evidence from retail and discount brokerage accounts. *Journal of Public Economics*, 88(1):419–442.

Barberis, N. and Xiong, W. (2009). What drives the disposition effect? an analysis of a long-standing preference-based explanation. *The Journal of Finance*, 64(2):751–784.

Barberis, N. and Xiong, W. (2012). Realization utility. *Journal of Financial Economics*, 104(2):251–271.

Boolell-Gunesh, S., Broihanne, M.-H., and Merli, M. (2009). Disposition effect, investor sophistication and taxes: Some french specificities. *Finance*, 30(1):51–78.

Brown, P., Chappel, N., da Silva Rosa, R., and Walter, T. (2006). The reach of the disposition effect: Large sample evidence across investor classes. *International Review of Finance*, 6(1-2):43–78.

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2009). Fight or flight? portfolio rebalancing by individual investors. *The Quarterly Journal of Economics*, 124(1):301–348.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, 20(4):425–451.

Cici, G. (2012). The prevalence of the disposition effect in mutual funds' trades. *Journal of Financial and Quantitative Analysis*, 47(4):795–820.

Constantinides, G. M. (1984). Optimal stock trading with personal taxes: Implications for prices and the abnormal january returns. *Journal of Financial Economics*, 13(1):65–89.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2):187–220.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Doering, P., Neumann, S., and Paul, S. (2015). A primer on social trading networks— institutional aspects and empirical evidence. *Working Paper. Presented at EFMA Annual Meetings 2015.*

Engelberg, J., Reed, A. V., and Ringgenberg, M. (2014). Short selling risk. *Western Finance Association (WFA).*

Engelberg, J. E., Reed, A. V., and Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2):260–278.

Feng, L. and Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, 9(3):305–351.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., and Rangel, A. (2014). Using neural data to test a theory of investor behavior: An application to realization utility. *The Journal of Finance*, 69(2):907–946.

Gemayel, R. and Preda, A. (2015). Does a scopic regime produce conformism? herding behavior among trade leaders on social trading platforms. *Working paper.*

Goldberger, A. S. (1964). *Econometric theory.* New York: John Wiley & Sons.

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Harrell, F. E. (2013). *Regression modeling strategies: with applications to linear models, logistic regression, and survival analysis.* Springer Science & Business Media.

Harrell, F. E., Califf, R. M., Pryor, D. B., Lee, K. L., and Rosati, R. A. (1982). Evaluating the yield of medical tests. *Jama*, 247(18):2543–2546.

Heimer, R. (2015). Peer pressure: Can social interaction explain the disposition effect? *Review of Financial Studies (Forthcoming).*

Henderson, V. (2012). Prospect theory, liquidation, and the disposition effect. *Management Science*, 58(2):445–460.

Hens, T. and Vlcek, M. (2011). Does prospect theory explain the disposition effect? *Journal of Behavioral Finance*, 12(3):141–157.

Ivković, Z., Poterba, J., and Weisbenner, S. (2005). Tax-motivated trading by individual investors. *The American Economic Review*, 95(5):1605–1630.

Jenkins, S. P. (2005). Survival analysis. *Unpublished manuscript, Institute for Social and Economic Research, University of Essex, Colchester, UK.*

Kahneman, D. (1992). Reference points, anchors, norms, and mixed feelings. *Organizational Behavior and Human Decision Processes*, 51(2):296–312.

Kahneman, D. and Riepe, M. W. (1998). Aspects of investor psychology. *Journal of Portfolio Management*, 24(4):52–65.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Kaustia, M. (2010). Prospect theory and the disposition effect. *Journal of Financial and Quantitative Analysis*, 45(3):791–812.

Knez, P., Smith, V. L., and Williams, A. W. (1985). Individual rationality, market rationality, and value estimation. *American Economic Review*, 75(2):397–402.

Knorr Cetina, K. (2003). From pipes to scopes: The flow architecture of financial markets. *Distinktion: Scandinavian Journal of Social Theory*, 4(2):7–23.

Lehenkari, M. (2012). In search of the underlying mechanism of the disposition effect. *Journal of Behavioral Decision Making*, 25(2):196–209.

Linnainmaa, J. T. (2010). Do limit orders alter inferences about investor performance and behavior? *The Journal of Finance*, 65(4):1473–1506.

Nolte, I. (2012). A detailed investigation of the disposition effect and individual trading behavior: a panel survival approach. *The European Journal of Finance*, 18(10):885–919.

Nolte, I. and Voev, V. (2011). Trading dynamics in the foreign exchange market: A latent factor panel intensity approach. *Journal of Financial Econometrics*, 9(4):685–716.

Norman, D. J. (2009). *CFDs: The Definitive Guide to Contracts for Difference*. Harriman House Limited.

Odean, T. (1998a). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Odean, T. (1998b). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, 53(6):1887–1934.

Richards, D. W., Rutterford, J., Kodwani, D., and Fenton-O'Creevy, M. (2015). Stock market investors' use of stop losses and the disposition effect. *The European Journal of Finance*, pages 1–23.

Seru, A., Shumway, T., and Stoffman, N. (2010). Learning by trading. *Review of Financial Studies*, 23(2):705–739.

Shapira, Z. and Venezia, I. (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance*, 25(8):1573–1587.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.

Strahilevitz, M. A., Odean, T., and Barber, B. M. (2011). Once burned, twice shy: How naïve learning, counterfactuals, and regret affect the repurchase of stocks previously sold. *Journal of Marketing Research*, 48:102–120.

Summers, B. and Duxbury, D. (2012). Decision-dependent emotions and behavioral anomalies. *Organizational Behavior and Human Decision Processes*, 118(2):226–238.

Weber, M. and Camerer, C. F. (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization*, 33(2):167–184.

Wegener, D. T. and Petty, R. E. (1995). Flexible correction processes in social judgment: the role of naive theories in corrections for perceived bias. *Journal of Personality and Social Psychology*, 68(1):36–51.

Yao, J. and Li, D. (2013). Prospect theory and trading patterns. *Journal of Banking & Finance*, 37(8):2793–2805.

Table 3.1: **Investment Universe Provided by the Anonymous Foreign Exchange Broker.** The following table lists all the currency pairs that are offered to traders on the Anonymous platform.

AUD/CAD	EUR/JPY
AUD/CHF	EUR/USD
AUD/JPY	GBP/CAD
AUD/USD	GBP/CHF
CAD/CHF	GBP/JPY
CAD/JPY	GBP/USD
CHF/JPY	NZD/JPY
EUR/AUD	NZD/USD
EUR/CAD	USD/CAD
EUR/CHF	USD/CHF
EUR/GBP	USD/JPY

Table 3.2: **Descriptive Statistics of Trades Executed by Trade Leaders on eToro During 2013.** The following table shows descriptive statistics of all trades executed by trade leaders during 2013. The **Financial Instruments** subgroups show the proportion of all trades where the underlying asset is a currency, commodity, index, or stock, respectively. The table also presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average number of lots a trader holds. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	2,640,972				
Number of Traders	=	77,476				
Financial Instruments				**Trade Close Type**		
Currencies	=	83.14%		*Manual*	=	62.76%
Commodities	=	11.21%		*Stop Loss*	=	22.04%
Indicies	=	3.60%		*Take Profit*	=	13.14%
Stocks	=	2.05%		*Rollover*	=	2.06%
	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	66.11%	175	6.08	34.18	1	3.61
Min	0.0%	1.0	0	1	0.02	1
Max	100%	400.0	347	14,672	282	71
St.Dev.	0.355	156.51	17.24	166.32	3.20	4.36

Table 3.3: **Descriptive Statistics of Trades Executed by Traders on Anonymous During From January 2011 to September 2013.** The following table shows descriptive statistics of all trades executed by traders from January 2011 to September 2013. The table presents several trading behavior attributes. **Long** represents the average proportion of trades that are long positions. **Leverage** is the average leverage ratio employed by a trader. **Time** is the average duration of a trade measured in days. **Annual Trades** and **Weekly Trades** are the number of annual and average weekly trades, respectively, per trader. **Instruments** is the number of different financial instruments traded by a trader.

Number of Trades	=	6,928,399
Number of Traders	=	22,545
Trade Close Type		
Manual	=	66.48%
Stop Loss	=	14.41%
Take Profit	=	19.11%

	Long	**Leverage**	**Time (days)**	**Annual Trades**	**Weekly Trades**	**Instruments**
Mean	47.00%	200	1.19	111.75	2.15	5.72
Min	0.0%	200	0	1	0.02	1
Max	100%	200	229.1	31,765	610.87	22
St.Dev.	0.164	0	3.39	382.02	7.35	4.65

Table 3.4: **Disposition Spread of Trade Leaders on eToro and Traders on Anonymous - No Trader Clustering.** The four panels in the following table represent the different trading platforms, assets, and time-frames used in the analysis of the disposition spread. The parameters *RG*, realized gain, *RL*, realized loss, *PG*, paper gain, and *PL*, paper loss are aggregated across all trades and traders prior to calculating the proportions of gains and losses realized, given by *PGR* and *PLR*, respectively. *DISP* and *DISP RATIO* represent the disposition spread and disposition ratio, respectively. Finally, the t-statisitc is presented to test for the significance of the disposition spread.

Panel A: eToro - All assets - From January 2013 to December 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	3,128	7,433	11,733	16,054	20,293	24,670	28,909	33,373	37,626	41,797	46,231	50,548	54,722	59,089
RL	1,905	4,541	7,175	9,816	12,374	15,141	17,880	20,464	23,030	25,569	28,280	31,001	33,517	36,393
PG	3,115	3,120	3,102	3,122	3,191	3,064	2,916	3,102	3,102	3,286	3,094	2,969	3,135	2,868
PL	4,499	4,501	4,532	4,552	4,610	4,541	4,221	4,685	4,525	4,600	4,640	4,510	4,729	4,221
PGR	41.85%	62.38%	76.26%	82.06%	85.52%	88.76%	90.76%	91.45%	92.21%	92.45%	93.65%	94.36%	94.49%	95.34%
PLR	26.26%	44.98%	58.33%	66.29%	71.74%	76.31%	80.59%	81.08%	83.19%	84.23%	85.36%	86.82%	87.24%	89.33%
DISP	15.59%	17.40%	17.93%	15.76%	13.79%	12.45%	10.17%	10.37%	9.02%	8.22%	8.28%	7.54%	7.25%	6.00%
DISP RATIO	1.73	1.52	1.35	1.26	1.20	1.17	1.13	1.13	1.11	1.10	1.10	1.09	1.08	1.07
t-statistic	-18.74	-24.70	-31.23	-32.71	-33.23	-34.83	-32.63	-36.13	-34.48	-33.69	-37.04	-36.74	-37.16	-34.30

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	55,264	154,244	251,732	352,896	445,360	547,560	646,198	747,248	845,886	938,509	1,042,444	1,141,160	1,238,868	1,335,578
RL	67,772	198,042	320,078	452,027	571,799	713,897	844,938	970,964	1,087,960	1,215,858	1,347,143	1,485,708	1,589,639	1,747,243
PG	833,017	835,434	822,391	828,329	832,224	821,547	795,648	804,490	803,136	873,713	852,843	779,050	831,317	748,787
PL	1,673,960	1,681,006	1,671,392	1,697,021	1,715,562	1,663,776	1,633,218	1,752,901	1,635,292	1,721,799	1,712,852	1,653,572	1,806,046	1,604,585
PGR	8.60%	19.19%	27.99%	34.73%	39.39%	45.12%	49.12%	51.54%	54.27%	54.72%	57.78%	61.70%	61.97%	65.41%
PLR	4.75%	11.63%	17.83%	22.91%	27.12%	31.86%	36.34%	37.49%	41.40%	42.36%	45.62%	47.88%	48.46%	53.19%
DISP	3.85%	7.56%	10.17%	11.82%	12.27%	13.25%	12.77%	14.06%	12.87%	12.37%	12.16%	13.82%	13.50%	12.22%
DISP RATIO	2.09	1.85	1.68	1.61	1.50	1.44	1.39	1.42	1.35	1.31	1.32	1.31	1.32	1.25
t-statistic	-113.81	-164.42	-198.90	-225.77	-234.78	-254.06	-247.30	-282.87	-263.01	-263.83	-265.47	-306.97	-311.95	-285.77

(continued)

Table 3.4 - Continued

Panel B: Anonymous - All assets - From January 2011 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	3,605	8,130	12,626	17,168	21,725	26,196	31,066	35,223	39,720	44,332	48,794	53,204	57,807	62,613
RL	1,721	4,011	6,309	8,573	10,919	13,179	15,667	17,745	20,097	22,384	24,673	26,907	29,282	31,714
PG	1,449	1,435	1,443	1,434	1,471	1,434	1,517	1,446	1,443	1,453	1,512	1,453	1,424	1,494
PL	4,496	4,507	4,519	4,509	4,493	4,539	4,383	4,529	4,548	4,552	4,470	4,472	4,598	4,431
PGR	53.77%	71.95%	84.59%	87.82%	89.46%	90.32%	91.23%	92.04%	91.78%	92.45%	93.06%	93.03%	92.90%	93.85%
PLR	28.71%	45.45%	57.79%	65.19%	70.24%	73.55%	76.55%	78.52%	79.68%	80.87%	82.20%	83.16%	83.78%	85.17%
DISP	25.06%	26.49%	26.80%	22.64%	19.22%	16.78%	14.69%	13.52%	12.10%	11.59%	10.86%	9.87%	9.12%	8.67%
DISP RATIO	2.52	1.99	1.66	1.40	1.32	1.25	1.21	1.18	1.16	1.15	1.16	1.13	1.11	1.11
t-statistic	-27.66	-37.39	-47.54	-47.11	-45.77	-44.61	-43.48	-43.71	-41.75	-42.97	-43.25	-41.51	-40.29	-41.38

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	86,684	217,640	348,199	478,432	610,563	740,746	881,173	999,132	1,135,315	1,265,503	1,395,837	1,527,147	1,655,037	1,798,274
RL	-79,971	-245,032	-413,465	-575,946	-748,657	-906,691	-1,091,677	-1,242,875	-1,431,144	-1,583,511	-1,752,499	-1,907,244	-2,079,438	-2,257,987
PG	127,673	126,356	127,233	125,215	126,702	126,175	139,138	126,795	123,348	120,878	136,488	135,440	122,578	140,745
PL	-934,734	-935,774	-937,786	-932,627	-939,505	-931,639	-926,258	-945,262	-943,415	-940,048	-945,243	-926,237	-940,121	-933,305
PGR	35.08%	55.88%	69.48%	76.19%	79.56%	82.74%	83.61%	85.96%	86.45%	87.64%	87.98%	88.72%	89.23%	89.60%
PLR	10.86%	23.70%	33.28%	41.09%	47.22%	51.92%	55.33%	58.88%	61.98%	63.45%	64.96%	67.47%	69.34%	69.95%
DISP	24.21%	32.18%	36.19%	35.10%	32.33%	30.82%	28.28%	27.08%	24.47%	24.20%	23.02%	21.25%	19.89%	19.65%
DISP RATIO	7.94	8.65	8.36	11.39	1.98	1.94	1.86	1.55	1.45	1.44	1.55	1.37	1.32	1.33
t-statistic	-225.04	-345.04	-463.24	-517.00	-532.82	-562.22	-557.97	-580.32	-557.93	-586.78	-587.66	-572.72	-563.93	-582.31

(continued)

Table 3.4 - Continued

Panel C: eToro - Common Currency Pairs - From January 2013 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	2,876	6,712	10,470	14,338	18,055	21,898	25,521	29,477	33,056	36,766	40,914	44,727	48,517	52,073
RL	1,807	4,205	6,545	8,973	11,227	13,725	16,129	18,478	20,714	22,996	25,693	28,058	30,290	32,817
PG	1,974	1,954	1,989	1,922	2,033	1,924	1,808	1,951	1,964	2,107	1,959	1,812	1,924	1,780
PL	2,754	2,766	2,778	2,794	2,820	2,802	2,578	2,875	2,881	2,831	2,848	2,830	2,795	2,630
PGR	47.59%	68.26%	81.15%	86.52%	89.00%	91.70%	93.23%	93.71%	94.17%	94.29%	95.34%	96.04%	96.12%	96.64%
PLR	33.50%	53.49%	67.02%	74.28%	78.95%	82.68%	86.03%	86.38%	87.67%	88.74%	89.73%	90.58%	91.41%	92.46%
DISP	14.10%	14.77%	14.13%	12.24%	10.05%	9.02%	7.20%	7.33%	6.50%	5.55%	5.61%	5.46%	4.71%	4.18%
DISP RATIO	1.57	1.41	1.24	1.18	1.13	1.11	1.09	1.09	1.08	1.06	1.06	1.06	1.05	1.05
t-statistic	-14.08	-18.96	-23.55	-25.30	-24.59	-26.18	-24.35	-26.96	-26.22	-24.19	-27.16	-28.84	-26.67	-26.10

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	53,055	139,663	226,927	317,898	399,739	486,881	574,757	666,292	744,507	826,429	921,764	1,013,736	1,100,832	1,184,934
RL	67,165	182,395	290,163	403,683	506,985	635,532	746,599	855,934	945,296	1,064,921	1,185,835	1,310,418	1,387,875	1,538,589
PG	512,791	504,554	505,904	486,517	514,623	486,394	480,366	485,028	518,058	531,856	544,288	480,807	496,187	458,825
PL	1,090,789	1,090,102	1,095,183	1,103,809	1,103,033	1,082,356	1,061,360	1,152,754	1,105,728	1,122,150	1,105,636	1,132,411	1,153,750	1,069,975
PGR	12.03%	25.44%	35.53%	43.99%	48.00%	54.58%	58.55%	60.56%	62.01%	63.09%	66.31%	69.34%	70.07%	72.91%
PLR	6.65%	15.17%	22.34%	28.55%	33.34%	38.68%	43.14%	43.76%	47.38%	49.28%	53.15%	54.37%	56.08%	59.73%
DISP	5.38%	10.27%	13.18%	15.44%	14.66%	15.90%	15.41%	16.80%	14.64%	13.81%	13.16%	14.97%	13.99%	13.18%
DISP RATIO	2.31	2.07	1.76	1.69	1.54	1.47	1.41	1.43	1.37	1.31	1.30	1.31	1.31	1.24
t-statistic	-109.60	-163.32	-199.25	-232.30	-228.67	-253.66	-254.84	-292.47	-263.68	-258.42	-257.54	-303.25	-292.76	-285.99

(continued)

Table 3.4 - Continued

Panel D: Anonymous - Common Currency Pairs - From January 2013 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	6,902	15,746	24,472	33,391	42,411	51,286	59,544	68,631	77,812	86,703	96,466	105,329	112,404	122,138
RL	3,306	7,752	12,189	16,712	21,200	25,715	30,016	34,526	39,059	43,548	48,595	53,201	56,616	61,740
PG	2,803	2,798	2,833	2,778	2,903	2,868	2,395	2,785	2,880	2,901	2,976	2,839	2,818	2,419
PL	9,725	9,759	9,710	9,783	9,821	9,739	9,580	9,800	9,885	9,928	9,734	9,685	9,895	9,778
PGR	54.38%	74.56%	87.30%	91.22%	93.07%	94.53%	95.99%	96.01%	96.34%	96.66%	96.88%	97.31%	97.47%	97.99%
PLR	23.04%	39.97%	52.61%	61.15%	67.10%	71.92%	75.57%	77.58%	79.07%	80.78%	82.88%	84.15%	84.85%	86.13%
DISP	31.34%	34.59%	34.69%	30.07%	25.97%	22.61%	20.42%	18.43%	17.27%	15.88%	14.00%	13.16%	12.62%	11.85%
DISP RATIO	3.14	2.44	1.80	1.55	1.41	1.33	1.28	1.24	1.22	1.20	1.17	1.16	1.15	1.14
t-statistic	-50.08	-70.71	-88.26	-89.94	-88.87	-87.67	-88.82	-87.27	-88.37	-87.89	-84.66	-85.57	-86.14	-87.66

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	157,094	395,886	631,923	876,642	1,118,536	1,361,151	1,588,382	1,834,028	2,081,792	2,324,484	2,597,256	2,846,159	3,021,068	3,304,364
RL	137,409	425,142	729,171	1,007,411	1,306,987	1,625,909	1,917,199	2,203,295	2,493,637	2,797,421	3,147,561	3,478,862	3,693,890	4,024,836
PG	190,122	188,573	191,800	187,473	191,508	192,547	174,227	188,083	201,781	184,474	225,628	203,187	192,535	174,862
PL	1,859,337	1,868,575	1,855,641	1,873,169	1,883,716	1,864,486	1,879,618	1,861,807	1,871,400	1,895,526	1,905,318	1,868,281	1,849,855	1,911,417
PGR	36.14%	58.45%	73.07%	80.11%	84.39%	87.23%	89.87%	90.56%	91.24%	92.40%	91.75%	93.15%	93.76%	94.74%
PLR	7.61%	18.66%	28.26%	35.56%	41.38%	47.38%	51.87%	55.31%	57.96%	60.34%	62.70%	65.42%	67.27%	68.35%
DISP	28.53%	39.80%	44.81%	44.55%	43.02%	39.85%	38.00%	35.24%	33.28%	32.06%	29.05%	27.74%	26.49%	26.39%
DISP RATIO	8.37	5.06	3.50	2.65	2.23	1.95	1.80	1.69	1.61	1.57	1.50	1.45	1.42	1.41
t-statistic	-341.05	-573.43	-795.43	-930.43	-1,023.79	-1,053.28	-1,108.83	-1,097.71	-1,104.09	-1,140.74	-1,074.33	-1,103.08	-1,100.73	-1,171.45

Table 3.5: **Disposition Spread of Trade Leaders on eToro and Traders on Anonymous - With Trader Clustering.** The four panels in the following table represent the different trading platforms, assets, and time-frames used in the analysis of the disposition spread. The parameters RG, realized gain, RL, realized loss, PG, paper gain, and PL, paper loss are aggregated for each trader individually prior to calculating the proportions of gains and losses realized, given by PGR and PLR, respectively. *DISP* and *DISP RATIO* represent the disposition spread and disposition ratio, respectively. Finally, the t-statisitc is presented to test for the significance of the disposition spread.

Panel A: eToro - All assets - From January 2013 to December 2013														
Parameters are calculated based on trade count.														
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	0.92	1.87	2.64	3.30	3.90	4.51	5.07	5.51	6.03	6.32	6.84	7.25	7.46	7.99
RL	0.56	1.14	1.62	2.02	2.38	2.77	3.13	3.38	3.69	3.87	4.19	4.44	4.57	4.92
PG	0.92	0.79	0.70	0.64	0.61	0.56	0.51	0.51	0.50	0.50	0.46	0.43	0.43	0.39
PL	1.32	1.13	1.02	0.94	0.89	0.83	0.74	0.77	0.72	0.70	0.69	0.65	0.64	0.57
PGR	21.55%	35.12%	43.10%	47.92%	50.86%	54.25%	56.71%	57.44%	58.81%	58.74%	60.51%	61.55%	61.26%	63.15%
PLR	16.65%	29.05%	37.26%	42.70%	46.62%	50.99%	55.16%	55.99%	58.76%	59.21%	61.59%	63.71%	63.87%	67.24%
DISP	4.90%	6.06%	5.84%	5.22%	4.24%	3.26%	1.54%	1.45%	0.05%	-0.47%	-1.08%	-2.16%	-2.61%	-4.10%
DISP RATIO	0.79	0.82	0.84	0.85	0.86	0.86	0.85	0.86	0.85	0.84	0.85	0.84	0.84	0.82
t-statistic	-0.12	-0.14	-0.15	-0.14	-0.12	-0.09	-0.05	-0.05	0.00	0.02	0.04	0.08	0.10	0.16
Parameters are calculated based on trade dollar value.														
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	16.25	38.87	56.67	72.62	85.53	100.01	113.24	123.47	135.52	141.99	154.33	163.58	168.92	180.70
RL	-19.93	-49.91	-72.06	-93.02	-109.81	-130.39	-148.07	-160.44	-174.30	-183.95	-199.44	-212.97	-216.74	-236.40
PG	244.94	210.54	185.15	170.45	159.82	150.05	139.44	132.93	128.67	132.18	126.26	111.68	113.35	101.31
PL	-492.22	-423.63	-376.29	-349.21	-329.46	-303.87	-286.22	-289.64	-261.99	-260.49	-253.58	-237.04	-246.25	-217.10
PGR	17.98%	30.18%	37.69%	42.41%	45.26%	48.91%	51.97%	52.19%	53.85%	53.63%	55.72%	57.21%	56.85%	59.53%
PLR	14.91%	26.63%	34.52%	39.81%	43.51%	47.97%	52.57%	52.81%	55.89%	56.13%	58.55%	60.87%	60.93%	65.02%
DISP	3.07%	3.54%	3.17%	2.60%	1.75%	0.94%	-0.61%	-0.62%	-2.04%	-2.50%	-2.83%	-3.66%	-4.08%	-5.49%
DISP RATIO	14.07	12.92	11.08	11.84	9.64	10.24	9.73	10.75	8.40	8.77	9.62	10.25	8.54	8.15
t-statistic	-1.08	-1.00	-0.83	-0.66	-0.44	-0.24	0.15	0.16	0.53	0.65	0.75	0.97	1.10	1.49

(continued)

Table 3.5 - Continued

Panel B: Anonymous - All assets - From January 2011 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	2.04	4.01	5.66	7.25	8.78	10.22	11.77	13.03	14.34	15.62	16.86	18.14	19.24	20.61
RL	0.97	1.98	2.83	3.62	4.41	5.14	5.94	6.56	7.26	7.89	8.52	9.18	9.75	10.44
PG	0.82	0.71	0.65	0.61	0.59	0.56	0.57	0.54	0.52	0.51	0.52	0.50	0.47	0.49
PL	2.54	2.22	2.03	1.90	1.82	1.77	1.66	1.68	1.64	1.60	1.54	1.52	1.53	1.46
PGR	36.30%	53.75%	63.73%	69.65%	73.27%	76.22%	78.35%	79.79%	80.97%	81.89%	82.71%	83.62%	84.45%	85.13%
PLR	23.14%	36.90%	45.54%	51.57%	56.40%	59.81%	63.32%	64.88%	66.84%	68.52%	70.04%	71.48%	72.48%	74.01%
DISP	13.16%	16.85%	18.18%	18.08%	16.87%	16.40%	15.03%	14.91%	14.13%	13.37%	12.67%	12.14%	11.97%	11.12%
DISP RATIO	1.18	1.26	1.28	1.29	1.27	1.27	1.24	1.25	1.24	1.23	1.21	1.20	1.21	1.19
t-statistic	-0.36	-0.51	-0.61	-0.67	-0.69	-0.72	-0.71	-0.75	-0.75	-0.75	-0.74	-0.75	-0.77	-0.75

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	49.02	107.40	156.20	202.11	246.76	289.05	333.83	369.58	409.89	445.80	482.24	520.76	550.82	592.00
RL	-45.22	-120.92	-185.48	-243.30	-302.57	-353.81	-413.58	-459.74	-516.70	-557.83	-605.46	-650.37	-692.06	-743.34
PG	72.20	62.35	57.08	52.90	51.21	49.24	52.71	46.90	44.53	42.58	47.15	46.19	40.80	46.33
PL	-528.60	-461.77	-420.70	-393.98	-379.70	-363.54	-350.91	-349.66	-340.61	-331.15	-326.56	-315.85	-312.88	-307.25
PGR	33.96%	51.59%	61.81%	67.93%	71.61%	74.77%	76.55%	78.57%	79.77%	80.85%	81.35%	82.40%	83.61%	83.89%
PLR	21.57%	35.12%	43.68%	49.60%	54.35%	57.76%	61.14%	62.76%	64.72%	66.46%	67.79%	69.30%	70.42%	71.84%
DISP	12.39%	16.47%	18.13%	18.33%	17.26%	17.01%	15.40%	15.80%	15.05%	14.39%	13.56%	13.10%	13.19%	12.05%
DISP RATIO	44.39	40.96	37.47	35.76	32.71	30.51	27.59	29.52	27.98	27.58	25.90	23.23	24.91	22.30
t-statistic	-2.68	-3.82	-4.66	-5.19	-5.34	-5.68	-5.53	-6.00	-6.04	-6.04	-5.94	-6.01	-6.29	-5.99

(continued)

Table 3.5 - Continued

Panel C: eToro - Common Currency Pairs - From January 2013 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	1.31	2.43	3.21	3.92	4.52	5.08	5.60	6.02	6.43	6.81	7.23	7.60	7.93	8.20
RL	0.82	1.52	2.01	2.45	2.81	3.19	3.54	3.77	4.03	4.26	4.54	4.77	4.95	5.17
PG	0.90	0.71	0.61	0.53	0.51	0.45	0.40	0.40	0.38	0.39	0.35	0.31	0.31	0.28
PL	1.25	1.00	0.85	0.76	0.71	0.65	0.57	0.59	0.56	0.52	0.50	0.48	0.46	0.41
PGR	31.81%	47.13%	54.54%	59.55%	61.64%	64.34%	66.18%	66.34%	66.83%	67.18%	68.11%	68.89%	68.97%	69.55%
PLR	25.73%	40.65%	49.08%	55.21%	58.74%	62.98%	66.95%	67.42%	69.44%	70.65%	72.46%	74.27%	75.24%	77.05%
DISP	6.08%	6.47%	5.46%	4.34%	2.90%	1.36%	-0.77%	-1.07%	-2.61%	-3.47%	-4.35%	-5.38%	-6.27%	-7.49%
DISP RATIO	0.72	0.75	0.77	0.79	0.80	0.80	0.79	0.80	0.79	0.79	0.79	0.79	0.78	0.77
t-statistic	-0.14	-0.15	-0.14	-0.12	-0.09	-0.04	0.03	0.04	0.09	0.13	0.17	0.21	0.26	0.31

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	24.17	50.55	69.65	86.87	100.10	113.00	126.05	136.01	144.72	153.14	162.88	172.30	180.01	186.51
RL	-30.59	-66.01	-89.06	-110.31	-126.96	-147.50	-163.74	-174.72	-183.75	-197.33	-209.54	-222.73	-226.94	-242.18
PG	233.58	182.61	155.27	132.94	128.87	112.89	105.35	99.01	100.70	98.56	96.18	81.72	81.14	72.22
PL	-496.86	-394.53	-336.14	-301.62	-276.22	-251.20	-232.77	-235.31	-214.94	-207.94	-195.37	-192.47	-188.66	-168.42
PGR	27.45%	41.84%	48.97%	54.31%	56.25%	59.44%	61.90%	61.75%	62.45%	62.59%	64.01%	65.32%	65.29%	66.66%
PLR	23.81%	38.38%	46.68%	52.85%	56.18%	60.66%	65.05%	65.06%	67.33%	68.29%	70.44%	72.21%	73.21%	75.58%
DISP	3.65%	3.46%	2.29%	1.47%	0.07%	-1.22%	-3.14%	-3.31%	-4.88%	-5.71%	-6.43%	-6.88%	-7.91%	-8.92%
DISP RATIO	7.52	6.61	5.58	6.28	5.22	5.32	4.54	6.20	4.50	4.15	4.55	4.96	4.46	3.51
t-statistic	-1.09	-0.88	-0.56	-0.35	-0.02	0.30	0.79	0.84	1.26	1.49	1.72	1.86	2.16	2.47

(continued)

Table 3.5 - Continued

Panel D: Anonymous - Common Currency Pairs - From January 2013 to September 2013

Parameters are calculated based on trade count.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	1.99	3.99	5.65	7.27	8.83	10.35	11.82	13.16	14.57	15.89	17.37	18.61	19.60	21.06
RL	0.95	1.96	2.82	3.64	4.41	5.19	5.96	6.62	7.32	7.98	8.75	9.40	9.87	10.65
PG	0.81	0.71	0.65	0.61	0.60	0.58	0.48	0.53	0.54	0.53	0.54	0.50	0.49	0.42
PL	2.80	2.47	2.24	2.13	2.05	1.97	1.90	1.88	1.85	1.82	1.75	1.71	1.73	1.69
PGR	34.42%	52.01%	62.03%	68.17%	71.76%	74.98%	77.73%	78.81%	79.94%	80.79%	81.97%	82.82%	83.42%	84.73%
PLR	21.29%	34.51%	43.05%	49.13%	53.57%	57.35%	60.71%	62.40%	63.97%	65.68%	67.60%	69.27%	69.92%	71.54%
DISP	13.13%	17.50%	18.97%	19.03%	18.19%	17.63%	17.02%	16.41%	15.97%	15.11%	14.36%	13.56%	13.51%	13.20%
DISP RATIO	1.24	1.34	1.34	1.35	1.34	1.32	1.32	1.30	1.30	1.28	1.27	1.25	1.25	1.25
t-statistic	-0.37	-0.54	-0.65	-0.72	-0.74	-0.78	-0.81	-0.82	-0.84	-0.84	-0.84	-0.83	-0.85	-0.88

Parameters are calculated based on trade dollar value.

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RG	45.25	100.19	146.00	190.94	232.90	274.66	315.33	351.69	389.93	426.07	467.59	502.91	526.90	569.81
RL	-39.58	-107.59	-168.47	-219.43	-272.14	-328.08	-380.60	-422.50	-467.07	-512.76	-566.66	-614.70	-644.25	-694.05
PG	54.77	47.72	44.31	40.83	39.88	38.85	34.59	36.07	37.79	33.81	40.62	35.90	33.58	30.15
PL	-535.63	-472.90	-428.72	-408.00	-392.22	-376.22	-373.14	-357.02	-350.52	-347.44	-343.02	-330.12	-322.63	-329.61
PGR	32.81%	50.78%	60.85%	67.19%	70.78%	74.06%	77.29%	78.31%	79.26%	80.24%	80.98%	82.03%	82.75%	84.35%
PLR	20.14%	33.24%	41.63%	47.58%	52.01%	55.61%	58.95%	60.71%	62.18%	63.93%	65.51%	67.25%	68.03%	69.47%
DISP	12.67%	17.54%	19.22%	19.61%	18.78%	18.45%	18.34%	17.60%	17.07%	16.31%	15.47%	14.78%	14.72%	14.89%
DISP RATIO	56.26	51.18	42.84	44.32	39.95	35.31	37.16	34.45	29.55	33.36	29.79	28.63	26.86	28.26
t-statistic	-2.54	-3.85	-4.72	-5.34	-5.58	-5.95	-6.39	-6.45	-6.59	-6.59	-6.59	-6.57	-6.72	-7.20

Table 3.6: **Disposition Effect of Traders Using the Cox Proportional Hazards Model.** The following table includes two panels, one for each data set based on the overlapping time frame and on the common assets traded on the two platforms. Each panel reports the results of three Cox Proportional Hazards Models. Model (1) uses only the *Gain* binary variable. Model (2) also includes the control variables *Long*, T/P, S/L, and *Leverage*, in addition to asset fixed-effects (Asset FE). Model (3) further incorporates trader random effects (Trader RE).

Panel A: eToro - Common currency pairs - From January 2013 to September 2013

	Model (1)				Model (2)				Model (3)			
	Coef.	OR	S.E.		Coef.	OR	S.E.		Coef.	OR	S.E.	
Gain	-0.042	0.959	0.002	***	0.021	1.021	0.002	***	0.27	1.31	0.002	***
Long					0.066	1.068	0.002	***	0.023	1.023	0.002	***
T/P					-1.255	0.285	0.022	***	-1.093	0.335	0.023	***
$T/P \times Gain$					0.665	1.945	0.022	***	0.645	1.906	0.023	***
S/L					-0.443	0.642	0.003	***	-0.355	0.701	0.003	***
$S/L \times Gain$					-0.212	0.809	0.006	***	-0.217	0.805	0.006	***
*Leverage*5					-1.09	0.336	0.078	***	-0.494	0.61	0.112	***
*Leverage*10					-0.284	0.753	0.071	***	-0.075	0.928	0.106	
*Leverage*25					0.078	1.081	0.071		0.301	1.351	0.105	***
*Leverage*50					0.719	2.052	0.071	***	0.697	2.008	0.105	***
*Leverage*100					1.11	3.036	0.071	***	1.154	3.171	0.105	***
*Leverage*200					1.993	7.335	0.071	***	1.774	5.894	0.105	***
*Leverage*400					2.631	13.883	0.071	***	2.493	12.1	0.105	***
Asset FE						✓				✓		
Trader RE										✓		
N		1,600,001				1,600,001				1,600,001		
Concordance		50.50%				72.90%				82.70%		

(continued)

Table 3.6 - Continued

Panel B: Anonymous - Common currency pairs - From January 2013 to September 2013												
	Model (1)				Model (2)				Model (3)			
	Coef.	OR	S.E.		Coef.	OR	S.E.		Coef.	OR	S.E.	
Gain	0.433	1.542	0.001	***	0.696	2.006	0.001	***	0.901	2.462	0.001	***
Long					-0.054	0.948	0.001	***	0.006	1.006	0.001	***
T/P					0.588	1.8	0.003	***	0.139	1.149	0.004	***
$T/P \times Gain$					-0.407	0.666	0.004	***	-0.002	0.998	0.004	
S/L					1.28	3.595	0.002	***	1.037	2.82	0.002	***
$S/L \times Gain$					-1.392	0.249	0.003	***	-1.169	0.311	0.003	***
Asset FE						✓				✓		
Trader RE										✓		
N		3,618,231				3,618,231				3,618,231		
Concordance		55.10%				63.10%				82.30%		

Chapter 4

Informed Trading on Social Trading Platforms: An Analysis of the Predictive Ability of Individual Traders in the Foreign Exchange and Commodities Markets

Abstract

We investigate the predictive ability of 41,072 position traders and 48,691 intraday traders in 19 different currency pairs and commodities on a social trading platform, where individuals have access to high quality order flow data. Based on the empirical methods developed by Henriksson and Merton (1981) and Fishe and Smith (2012), we use an unconditional test and identify around 50% of position traders as informed; however, when we condition on the state of the market, this proportion drops between 0.11% and 1.31%, indicating that few position traders possess the skill to correctly predict future price movements in both upward and downward trending markets. Regarding intraday traders, we identify around 15% of the sample as informed. We find that trading characteristics such as leverage, limit orders, equity used, trade position, trade duration, trading frequency, and number of different assets traded offer significant explanatory power about who is informed, especially when using realized profits as a basis to determine success.

4.1 Introduction

One of the most intriguing puzzles in finance is to identify informed market participants and understand the drivers behind their superior predictive ability. According to Fishe and Smith (2012), informed traders are "those whose actions show they hold valuable short-term price information." These actions are reflected in what is known as order flow, which includes the details of transactions between traders and brokers. As such, informed trading is associated with how prices respond to order flow, where steady profits may be a good indicator of who is informed (Fishe and Smith, 2012).

In foreign exchange, the decentralized structure of the market and the lack of aggregate order flow data have often raised the question of whether information differentials could allow traders to place informed trades, which would consequently enhance price discovery (Goodhart, 1988; Lyons, 1997). While the conventional argument is that all participants in the foreign exchange market have access to the same publicly disclosed information with virtually no potential for private information, some researchers including Lyons (2001) have argued that there exist several channels, such as order flow, through which private information plays a valuable role. Several early studies such as Goodhart (1988), Lyons (1997), and Peiers (1997) discuss how private data on order flow in the foreign exchange market may result in information differentials that can be advantageously used by brokerage firms and money managers in order to gauge the fundamental value of currencies. Covrig and Melvin (2002) present empirical evidence supporting this view, whereby Japanese banks are found to have a certain degree of price leadership during periods of significant information differential regarding order flow. Similarly, Marsh and O'Rourke (2005) examine the information content of customer order flow at a top European commercial bank, and find significant correlation between order flow and changes in exchange rates, which suggests that order flow contains valuable information. More recently, Nolte and Nolte (2012, 2016) investigated the information contained in the trading activity of around 2,000 individual retail traders on the OANDA FXTrade platform, and found important non-public information that can be used for short-term exchange rate forecasting. The evidence presented by the authors supports the argument that retail foreign exchange traders cannot be wholly dismissed as noise traders, and that their aggregate information processing ability generates additional predictive information.

Nevertheless, the scope of early studies was confined due to the limited access to data, which prevented in-depth analysis of individual trader behavior in the foreign exchange market (Lyons, 1995). Hence, most studies focused either on long-term macroeconomic dynamics of exchange rates (Iwatsubo and Marsh, 2014; MacDonald and Marsh, 2004; Mark, 1995), the microstructure of the foreign exchange market (Evans and Lyons, 2002; Lyons, 2001, 1995), the performance of institutional currency traders and fund managers (Melvin and Shand, 2011; Froot et al., 2011; Pojarliev and Levich, 2010; Marsh and O'Rourke, 2005; MacDonald and Marsh, 1996), or on the predictive power of technical analysis (Abbey and Doukas, 2012; Menkhoff and Taylor, 2007; Osler, 2003; Curcio et al., 1997).

The restricted access to order flow data on individual currency traders has created a significant gap in the literature on the predictive ability of these traders (Fan and Lyons, 2003). Consequently, many studies on informed trading and the predictive ability of individual traders focus on the futures markets — since information was more readily accessible from the Commodity Futures Trading Commission (CFTC) — and on individual stock traders.

Recent technological innovation has revolutionized the way individuals trade online, and has created a unique environment, such that what was once privately held order flow data is now publicly and freely disclosed on social trading platforms (STPs) in aim of providing participants with a higher degree of information transparency. This is the product of social trading, which is a novel concept that combines the traditional online trading model with the tools and features of social media networks. Every trade that is executed by all participants on the platform is publicly disclosed, and anyone can access the details of these transactions. A STP allows participants to communicate, collaborate, and even copy each other's trades in real-time using a mirror trading algorithm. Trading on STPs is done through a contract for difference (CFD), which is an electronic contract between a trader and a CFD provider that requires the trader to relinquish physical possession of the underlying asset for a contract with the CFD provider that offers an identical economic exposure (Norman, 2009). The high level of transparency on STPs enables participants to constantly and reciprocally scrutinize each other's trading activities, an environment known as a "scopic regime" (Knorr Cetina, 2003). Some of the information that is published by the STP typically includes a trader's biography, advertised trading strategy, posts, historical trades, and current portfolio holdings.

The reason why participants agree to share their private information with the entire social trading network is because STPs encourage participants to build a reputation in order to attract potential copiers, and offer compensation schemes that allow a trader to earn a performance fee based on the profits generated for his copiers. Given this highly informal principal-agent relationship, participants on STPs can be divided into two main groups, which we label as trade leaders and investors (or copiers). The former are generally experienced traders who manage the capital allocated to them by the latter in return for monetary compensation that may be directly or indirectly linked to performance. Doering et al. (2015) provide an extensive overview of the different compensation schemes offered by STPs. An investor can allocate his capital using the mirror trading algorithm offered by the platform by easily and explicitly copying the trades of others with a click of a button, thus receiving a price identical to that received by the copied trade leader. Hence, all future trades executed by a copied trade leader are automatically replicated in the investor's account. Moreover, the relationship between trade leaders and investors is entirely informal since investors have the liberty to terminate the copying relationship at any time and without any repercussions. Similarly, trade leaders are not directly penalized should they go rogue or deviate from their advertised trading strategy. Nevertheless, our study focuses on the predictive ability of trade leaders, who execute original trades based on their own analyses and strategies. Hence, we define a trade leader as an individual who only personally enters trades into the STP during the period of study, and refrains from *explicitly* copying others using mirror trading.

To the best of our knowledge, this is the first paper to investigate the predictive ability of individual foreign exchange traders under a scopic regime, where traders have access to high quality order flow data. We examine the propensity of a trader to be informed (i.e. the ability to correctly predict future price movements), given that there are virtually no obstacles in obtaining high quality information in real-time. We do not focus our analysis on the traders' ability to generate positive net profits, but rather on their ability to incorporate information contained in the order flow when predicting the direction of future price changes. This differentiates our study from early research done on the predictive power of technical analysis, which focuses solely on past price movements and a selection of technical indicators (Abbey and Doukas, 2012). Furthermore, it resonates the work of Hayley and Marsh (2015) on the performance, and learning ability of currency traders in a traditional trading environment, and builds on the empirical evidence of Nolte and Nolte (2016), who show that the information contained in the *aggregate* order flow of individual traders has significant predictive power.

A key challenge in this study is to select a proper measure of a trader's ability to *predict* future price movements. To elaborate, consider a trader who has correctly predicted future price movements in nine out of ten trades. If we use the proportion of successful trades as a measure of predictive ability, then one may consider this trader to be highly informed about the direction of future price changes. Now assume that the trader realized a gain of \$1 in each of the successful trades, and a loss of $-$\$10 in the tenth trade. If we consider overall profitability as a measure of predictive ability, then this trader is deemed uninformed. This dilemma becomes further complicated if we do not take into account the size of the gain or loss relative to a trader's wealth. For instance, a given dollar profit may be a significant success to a small trader, but would be considered a mediocre return for a large trader. Moreover, if the scenario were reversed where the trader has nine small losses of $-$\$1 and one large gain of \$10, then this trader's overall profitability may have been simply due to luck.

The above example illustrates how success measured using dollar values may be a misleading indicator of predictive ability, whereby a trader may be able to correctly forecast future price movements, but cannot achieve positive net profits. We highly stress on the point that overall profitability and predictive ability are two very different concepts, which should not be confused with each other. The former assesses a trader's performance and returns generated, while the latter assesses a trader's ability to correctly predict future price changes. In response to this issue, and given the limitations of our data set[1], we adopt some of the statistical methods developed by researchers on informed trading in the futures markets, such as Henriksson and Merton (1981) and Fishe and Smith (2012). Specifically, we use multiple definitions of informed trading based on binary profit rules in order to identify individuals with superior predictive ability and examine their trading characteristics. While binary profit rules may not be flawless, they resolve many of the issues that arise from using dollar values, as we discuss later in the methodology section.

[1]Our data set does not include the account balance of each trader, thus it is impossible for us to calculate alternative performance metrics such as return on investment.

Based on the definition of a trade leader, we investigate the effect of the scopic regime governing STPs on the predictive ability of individual traders. We use a data set from the highly popular eToro STP and classify over 700 thousand transactions executed by 41,072 position trade leaders — traders who keep positions open for more than one trading day — and over 1.7 million transactions executed by 48,691 intraday trade leaders in 19 different assets during 2013. These assets comprise of 16 currency pairs and three commodities. We adopt empirical techniques similar to those proposed by Henriksson and Merton (1981) and Fishe and Smith (2012) in order to identify trade leaders as either position informed, intraday informed, momentum, contrarian, or uninformed.

First, we use two profit rules based on unrealized profits (or position profits) and realized profits (or daily trading profits), separately, to assess whether position trade leaders are informed. In addition, we apply for each profit rule an unconditional test and a conditional test similar to the method proposed by Henriksson and Merton (1981) (denoted as HM test), where the former is a binomial test for the expectation of being profitable more than 50% of the time, and the latter tests whether traders are able to predict movements in prices in both upward and downward trending markets.

Second, we analyze intraday profits, and the relationship between position direction and past price movements in order to identify intraday trade leaders as either informed, momentum, contrarian, or uninformed. Since we are dealing with thousands of trade leaders, which results in thousands of test statistics, a multiple-testing problem arises where some tests may be significant due to chance. In order to control for these luck events, we use the false discovery rate (FDR) method developed by Benjamini and Hochberg (1995), where we apply a 5% critical value.[2]

For position trade leaders, the unconditional test identifies around 50% of these individuals as informed, indicating that half of position traders have profitably executed more than 50% of their trades. When we apply the HM test, the proportion of trade leaders that are identified as position informed drops between 0.11% and 1.31%. This suggests that very few position trade leaders possess the skill to correctly predict price changes in both upward and downward trending markets. In order to examine the characteristics of informed position trade leaders, we use a

[2]Fishe and Smith (2012) discuss how the statistical techniques of earlier studies did not make any allowance for the multiple-testing problem.

series of logistic models where the dependent binary variable indicates whether a trade leader is informed depending on the profit rule and test used. The independent variables are averaged for each trade leader and include the leverage used, percentage of trades that are limit orders, the natural log of the amount of equity used, the mean duration of a trade, the trading frequency, and the number of different assets traded. The models based on the daily trading profits rule have a superior fit, hence we focus the discussion on these results. In particular, individuals identified as position informed under the unconditional test tend to use higher leverage, apply limit orders to realize gains and limit losses, use less equity per trade, are generally successful in long trades, have longer trade durations, trade less frequently, and trade in multiple assets. When we analyze the characteristics of traders identified as informed under the HM test, we find that these individuals use less leverage, employ limit orders effectively, use more equity per trade, are able to short sell profitably, have long trade durations, trade more frequently, and trade in multiple assets.

With respect to intraday trade leaders, we identify around 15%, 49%, 29%, and 0.3% of the total sample as informed, momentum, contrarian, and uninformed, respectively.[3] We also examine the characteristics of these types of intraday traders using logistic regressions, and find the highest explanatory power for the intraday informed model. Specifically, we find that intraday informed trade leaders use relatively less leverage, employ limit orders to automatically realize gains and minimize drawdown, use more of their equity in each trade, are more successful in short trades, have relatively longer trade durations, trade more frequently, and diversify their trades in multiple assets.

Research on informed trading in the foreign exchange market has been very limited, the main hurdle being access to high quality order flow data, not only for academics, but more importantly for retail traders. This has prevented earlier studies from investigating how order flow data affects the predictive ability of individual traders. Social trading mitigates this issue by offering participants on STPs a vast amount of high quality information on order flow, thus allowing us to explore how these individuals incorporate this information into their trading decisions. Our findings provide insight about whom, if anyone, is informed in the foreign exchange and commodities markets — given that order flow data is readily accessible to all

[3]The reason why these percentages do not add up to 100 is because there is an additional category of traders who are known as random or noise traders; however, we do not include them in our discussion and analysis.

participants — and about the trading characteristics of these individuals.

We find that under a scopic trading regime, many individuals trade profitably more than half of the time. However, very few trade leaders possess the ability to correctly predict price movements in both upward and downward trending markets. This suggests that most foreign exchange and commodities trade leaders adopt short term trading strategies that are specific to the current state of the market, but fail when there are trend reversals.

The remainder of this paper is organized as follows. Section 4.2 presents the literature on informed trading. In section 4.3 we discuss the methodology used. Section 4.4 describes the data and variables. We discuss the results in section 4.5. Finally, section 4.6 concludes the paper.

4.2 Literature Review

The literature on the predictive ability of individual foreign exchange traders is very sparse, and most early studies focus on the predictive power of technical analysis due to the popularity of technical indicators among currency traders. Park and Irwin (2007) conduct a comprehensive review of the empirical papers and find that 24 out of 38 studies conclude that technical analysis can generate annual profits between 5% and 10%. Nevertheless, these studies do not examine the predictive ability of individual currency traders, but instead assess how technical indicators perform when applied to exchange rates. Abbey and Doukas (2012) argue that these studies suffer from various biases such as *ex-post* selection of trading rules, data snooping, and improper accounting of transaction costs. In response to the ambiguity of earlier studies, the authors use a data set of 428 individual currency traders from March 2004 to September 2009, and use the four most popular technical indicators to explain performance. They find that their model explains the cross-section of daily net returns of individual traders. Their results also show that individuals who trade based on the most popular technical indicators tend to underperform relative to those who steer away from these indicators. Nevertheless, the literature on the predictive ability of currency traders is limited to technical analysis, which is only one of many strategies that may be used in practice. Thus, focusing solely on technical trading rules would offer an incomplete assessment of the skills of these traders.

In a more recent study, Hayley and Marsh (2015) examine the performance and learning ability of almost 100,000 retail currency traders on a leading trading platform and report several main findings. First, they find significant heterogeneity in trader skills. Second, they find that traders are more likely to cease trading after experiencing a loss, and that this reaction is more pronounced among traders who are likely to be learning the most. Third, individuals trade more frequently and in larger volumes after receiving a positive signal. Fourth, despite the evidence they find for learning ability, the authors show that even highly experienced traders perform poorly. Finally, the authors find evidence of deterioration in performance with experience, which they interpret as "traders learning to fail due to irrational learning."

Another study by MacDonald et al. (2009) uses survey data from December 1991 to July 2006 of individual forecasts of three major currency pairs from the Financial Market Survey (Finanzmarkttest) of the Centre for European Economic Research (ZEW) in Mannheim, Germany. Around 75% of participants in the survey are professionals who work in the banking or bank-related sectors. The authors conclude that some traders possess superior forecasting ability across currency pairs, which stems from their knowledge and use of fundamentals to explain exchange rate behavior, as indicated by more accurate interest rate forecasts. In addition, their study shows that individuals with superior forecasting skills are more experienced. However, as Frankel and Froot (1987) state in their own survey study, "Economists generally distrust survey data. It is a cornerstone of positive economics that we learn more by observing what people do in the marketplace than what they say." Hence, using actual transaction data overcomes this concern.

Studies on informed trading in the futures markets have provided theoretical insight about the trading motives of individual traders. The notable risk premium theory developed by Keynes (1930) and Hicks (1946) supports the argument that rational futures speculators would only enter the market if expected profits are positive. Moreover, since futures trading is a zero-sum game, this consequently means that expected profits for hedgers would be negative after accounting for transaction costs. It follows that if the majority of hedgers hold long positions in the underlying asset and hedge by shorting futures contracts, futures prices will decrease below expected spot prices, which provides profitable long opportunities for speculators. Conversely, if hedgers hold short positions in the underlying asset and long positions in futures contracts, then speculators can expect to make profits by shorting futures contracts. The empirical evidence regarding this theory has been mixed.

Many studies have presented evidence in support of this theory, showing that speculators earn positive profits. Early studies including Hirshleifer (1988), Bessembinder (1992), and De Roon et al. (2000) study risk pricing in the futures and assets markets, and find that residual risk does not completely explain futures returns. This is consistent with the hedging-pressure theory, indicating that hedgers pay risk premiums to transfer non-marketable risks in the futures markets. Leuthold et al. (1994) examine nine years of daily commitments for large traders in the frozen pork bellies futures market and find that these traders earn significant profits. The authors show that these traders possess the ability to correctly forecast future price movements, thus can accumulate invaluable experience and wealth over time. Using the commitments of traders reports, Wang (2001) examines position-based sentiment by trader type in six actively traded agricultural futures markets, and finds that large speculator sentiment is a good indicator for price continuation, large hedger sentiment indicates the opposite, and small trader sentiment does not hold any significant forecasting value. Hence, traders can generate significant profits by buying when large speculators are bullish and large hedgers are bearish, or by selling when large speculators are bearish and large hedgers are bullish. Dewally et al. (2013) use a data set of transactions by large traders in the crude oil, gasoline, and heating oil futures markets, and find evidence in support of the risk premium hypothesis. Specifically, the authors find that hedgers exhibit large losses, while speculators generate significantly positive profits. In addition, individual traders generate profits when they take positions opposite to those of hedgers in aggregate. The authors argue that the trading profits of speculators are mainly driven by their use of strategies that exploit the risk premium. Furthermore, Fishe and Smith (2012) investigate trader positions from 2000 to 2009 for 12 futures markets, and identify two types of informed traders; those who hold intraday information, and the overnight informed, who are traders holding information about next day prices. They find that intraday informed traders hold the best signals for price changes in the near future (short horizon), and attempt to exploit this information in their trades. With respect to overnight informed traders, the authors find that these individuals process information very efficiently.

While there is substantial evidence in support of the risk premium theory, several studies have reported opposing findings. Fama and French (1987) show that for many commodities, basis variances that are large in absolute terms are in fact small relative to the variances of realized premiums and changes in sport prices. Thus, large variances of realized premiums suggest that the average premiums that are perceived to be economically significant are generally insufficient to conclude that expected premiums are non-zero. Kolb (1992) examines a data set of 980,800 daily settlement prices in 29 commodities from 1957 to 1988, and finds that most commodities do not exhibit a risk premium. Hartzmark (1987) also provides evidence of commercial futures traders (or hedgers) earning small positive profits, while non-commercial traders (or speculators) experiencing losses. In his follow up study, the author also finds that the proportion of traders exhibiting consistent forecasting ability is no more than one would expect due to chance (Hartzmark, 1991), and that traders with superior forecasting ability could only be found in the pork bellies market, which is generally characterized with high levels of excess speculation (Peck, 1980). As such, he concludes that trader performance is essentially determined by luck.

Studies on individual stock traders have proposed alternative arguments derived from behavioral models, which challenge the risk premium and luck theories. For instance, Odean (1998a) analyses the trading records of 10,000 accounts at a large discount brokerage, and finds that these individuals exhibit the disposition effect such that these investors have the tendency to hold on to losing investments too long and sell winners too soon. Moreover, Odean (1998b, 1999) finds evidence of overconfidence among individual investors, which results in lower expected utility, and shows that when information is costly to acquire, individuals who choose to pay for information trade more frequently but perform worse than those who choose not to acquire the information. Supporting evidence is also presented by Barber and Odean (2000), who show that investors who trade frequently tend to underperform their peers. Moreover, Barber and Odean (2008) find evidence showing that investors exhibit attention-based buying patterns, which lead to low returns. While the evidence provided above shows how behavioral biases hamper one's ability to make informed decisions, several researchers have presented arguments to rationalize trader behavior. For instance, Bikhchandani et al. (1992) argue that investors may rationally decide to herd if they believe that other market participants possess private information or superior investment skills. Moreover, Mahani and Bernhardt

(2007) and Linnainmaa (2011) propose models where investors rationally choose to speculate on price movements in hopes of learning whether they are able to trade profitably, knowing that the majority of traders lose money through speculation.

Based on the findings and arguments presented above, we expect that despite potential behavioral biases, an environment with high levels of transparency regarding order flow information should increase the overall prospects of informed trading.

4.3 Methodology

Researchers have questioned whether some individuals possess the ability to predict future price movements correctly and consistently, and have proposed empirical frameworks to identify them (Hartzmark, 1991; Leuthold et al., 1994; Fishe and Smith, 2012). In this study, we follow a methodology similar to that used by Fishe and Smith (2012) to identify informed trade leaders. We define the sequence of positions held by a trade leader in asset k on day t as $\{OI^k_{0,t}, OI^k_{1,t}, \ldots, OI^k_{J_k,t}\}$, where a positive value indicates a long position while a negative value indicates a short position. A trade leader opens a position $OI^k_{0,t}$, and after J_k trades he is left with position $OI^k_{J_k,t}$. Note that each closed trade in a CFD is essentially made up of two positions, a long (short) position to open the trade followed by a short (long) position — with the same amount of the underlying asset — to close the trade. Since the data used in this study includes all closed positions by trade leaders, we are able to observe intra-day position changes. Aggregating across all trades ($j = 1, 2, \ldots, J$) and assets ($k = 1, 2, \ldots, K$) on day t, we express profit as

$$\pi^*_t = \sum_{k=1}^{K} \sum_{j=0}^{J_k} OI^k_{j,t} \left(P^k_{j+1,t} - P^k_{j,t}\right), \tag{4.1}$$

where $P^k_{j,t}$ is the price of asset k at the time of trade j. The initial price of the asset that is bought or sold on day t is given by $P^k_{0,t}$, and the final price on that day, $P^k_{J_k+1,t}$, is the closing day price of the asset. Equation 4.1 can be rewritten as

$$\pi^*_t = \sum_{k=1}^{K} OI^k_{0,t} \left(P^k_{J_k+1,t} - P^k_{0,t}\right) + \left(OI^k_{J_k,t} - OI^k_{0,t}\right)\left(P^k_{J_k+1,t} - P^k_{*,t}\right), \tag{4.2}$$

where $P^k_{*,t}$ signifies a reference price, typically the price at which the CFD is closed.

Equation 4.2 expresses daily profits as a function of observable variables and one unobservable variable, $P^k_{*,t}$. Dropping the j subscript renders the above equation into the following

$$\pi^*_t = \sum_{k=1}^{K} OI^k_{t-1} \Delta P^k_t + \Delta OI^k_t \left(P^k_t - P^k_{*,t} \right) \tag{4.3}$$

where $\Delta P^k_t = P^k_t - P^k_{t-1}$ represents the change in end of day closing prices for the k^{th} asset, and $\Delta OI^k_t = OI^k_t - OI^k_{t-1}$ is the change in position direction between day $t-1$ and t. The first term in equation 4.3 is called the *position profit* or unrealized profit, which measures the profit if a trader keeps a position open until the next trading day. The second term represents the *trading profit* or realized profit, which is the profit resulting from a change in position direction (i.e. closing of a trade). To illustrate, consider the example where a trader buys an asset for 50 at time $t-1$, and the asset rises in value to 60 at time t. Since the position is still open then the second term in the above equation is zero as ΔOI^k_t is zero, which leaves a position profit of 10. Now assume that between times $t-1$ and t, the price of the asset rises and the trader sells it for 80. By inserting these numbers into the above equation, the overall profit would be equal to 30, which is essentially the selling price less the initial price.

4.3.1 Measures of Position Trading Predictive Ability

We use binary profit-based measures of success similar to those used by earlier studies, such as Hartzmark (1991), Leuthold et al. (1994), and Fishe and Smith (2012). In particular, we specify two profit rules using the binary variable θ in order to assess the success of a trade as follows:

1. Position profits: $\theta^p_t = \begin{cases} 1, & \text{if } \sum\limits_{k=1}^{K} OI^k_{t-1} \Delta P^k_t > 0 \\ 0, & \text{otherwise} \end{cases}$

2. Daily trading profits: $\theta^c_t = \begin{cases} \text{undefined}, & \text{if } \sum\limits_{k=1}^{K} \left| \Delta OI^k_{t-1} \right| = 0 \\ 1, & \text{if } \sum\limits_{k=1}^{K} \Delta OI^k_{t-1} \Delta P^k_t > 0 \\ 0, & \text{otherwise} \end{cases}$

The position profits variable, θ^p_t, accounts for unrealized profits prior to a trade being closed, and it is equal to one if the net open interest of a trader on a specific day is positive. In other words, the position profits rule measures the proportion of days a position was profitable (i.e. exhibited an unrealized gain) prior to it being closed. Conversely, the daily trading profits variable, θ_t^c, only considers days when a trade has been closed and the gain or loss is realized. We use the term "daily" in order to differentiate this measure from the intraday trading profits. While some early studies, such as Leuthold et al. (1994), only consider actual trading profits as an indicator of success, this study considers both unrealized and realized profits separately as measures of a trader's predictive ability.[4] As such, a successful trading decision means that either θ_t^p or θ_t^c is equal to one, which indicates that the trade is profitable based on the closing prices on day t. The profit rules discussed above aggregate position profits and trading profits daily, hence, a large position taken in an asset may override the gains or losses of smaller positions in the same asset, on the same day.

In addition to the drawbacks mentioned earlier regarding the use of dollar profits as a measure of success, binary profit rules are more favorable than using actual dollar profits due to the fact that the average daily profits of traders are not normally distributed, which may lead to inappropriate statistical inferences and hypothesis tests (Cressie, 1980). Using a binary measure of success allows us to better control for the presence of kurtosis, leading to more accurate detection of informed traders (Fishe and Smith, 2012). Nevertheless, Fishe and Smith (2012) argue that, despite the benefits of using binary measures of success, we may fail to identify some types of informed traders, specifically, 1) those who profit from skewness by sacrificing small losses in hopes of realizing sizable gains, and 2) those who are informed only infrequently and hold positions for only a few days. Given these arguments, the results obtained in this study represent only a subset of the informed trade leader population.

To implement the abovementioned procedure, we virtually close all positions using end-of-day closing prices in order to obtain the daily unrealized profit for each position. Next, we aggregate positions for each trader, within each asset and on each day, then we test the null hypothesis that the trader is successful half of the time. Specifically, we test $\mathrm{H}_0: E(\theta_t^p) = 0.5$ for position profits and $\mathrm{H}_0: E(\theta_t^c) = 0.5$

[4] Leuthold et al. (1994) argue that realized profits represent the ultimate decision of a trader; however, analyzing position profits as well allows us to properly assess the profitability of passively managed accounts.

for daily trading profits. This is called the unconditional test to identify informed traders. As such, a trader who randomly places trades is expected to be profitable only 50% of the time, given that there is no systematic bias in daily prices of the assets traded. Nevertheless, some traders may benefit from price trends, as described by Moskowitz et al. (2012), hence we also conduct the test proposed by Henriksson and Merton (1981), which we call the HM test. The latter is a conditional test where the null hypothesis of no informed trading is defined as

$$\mathrm{H}_0 : \Pr(i \in Long|\pi_i^L > 0) + \Pr(i \in Short|\pi_i^S > 0) = 1, \tag{4.4}$$

where i is a trade leader, π_i^L are the gains or losses contingent on the trades being long positions, and π_i^S are the gains or losses contingent on the trades being short positions. A trader is considered to be informed if both his long and short positions are profitable more than 50% of the time, such that the combined probabilities in equation 4.4 exceed one. This means that traders are informed if they can correctly identify and trade profitably in both upward and downward market trends. As a robustness check, we also conduct the HM test using a logistic model (Hartzmark, 1991; Leuthold et al., 1994), which is expressed as:

$$\log\left(\frac{Pr\left(z(t)=1\right)}{Pr\left(z(t)=0\right)}\right) = \alpha + \beta U(t), \tag{4.5}$$

where $z(t)$ is a binary variable that is equal to one if the price of the underlying has increased between time t and $t+1$, and zero otherwise. The parameter $U(t)$ is also a binary variable that indicates the trader's prediction at time t, and is equal to one if the position is long, and zero if it is short. The coefficient of β is equal to zero when the trader possesses no forecasting ability. If β is significantly greater than zero, this indicates that the trader is informed and can differentiate between upward and downward trending markets, and if β is significantly less than zero, this means that the trader possesses inferior forecasting ability. The results obtained based on the logistic model are very similar to those obtained from applying the Fisher exact test to the null hypothesis in equation 4.4, hence we do not report these results to avoid repetition.

The unconditional and HM tests compliment each other in the sense that the unconditional test is sensitive to the success rate, while the HM test is focused more on the relationship between trade direction and profit. Nevertheless, each test adopts a different definition of "informed trading," thus the individuals identified as informed under each approach may not be the same and may have entirely different trading characteristics.

4.3.2 Measures of Intraday Predictive Ability

In the previous section, we discussed how to identify position informed trade leaders by analyzing the daily profits of trades that have a duration greater than one trading day. Nevertheless, a trade leader may decide to adjust positions during the day, especially if his trading strategies or private information are time sensitive. As such, we identify intraday informed traders, and distinguish them from other types of intraday traders based on position information and past price movements. In the spirit of Fishe and Smith (2012), we categorize intraday trade leaders into one of four types: informed, uninformed, momentum, and contrarian.[5] Informed trade leaders open profitable positions prior to price changes, whereas uninformed trade leaders open positions that are unprofitable given future prices. Momentum and contrarian trade leaders execute trades in response to past price changes, such that momentum traders open positions in the same direction as past price change, while contrarian traders open positions in the opposite direction (Conrad and Kaul, 1998).

In order to separate trade leaders into the abovementioned types, we define a binary measure of success to determine the profitability of intraday trades. Specifically, we apply the following rule:

$$\text{3. Intraday trading profits: } \theta_t^d = \begin{cases} \text{undefined}, & \text{if } \sum_{k=1}^{K} \left|\Delta OI_t^k\right| = 0 \\ 1, & \text{if } \sum_{k=1}^{K} \Delta OI_t^k (P_t^k - P_{o,t}^k) > 0 \\ 0, & \text{otherwise.} \end{cases}$$

The intraday trading profits variable, θ_t^d, indicates whether a position that has been opened and closed in the same day is profitable. Both informed and momentum trade leaders would exhibit $E(\theta_t^d) > 0.5$, while uninformed and contrarian trade leaders would exhibit $E(\theta_t^d) < 0.5$. In order to separate these types of traders, we

[5]Fishe and Smith (2012) identify two additional types of intraday traders, which they label as large liquidity demanders and large liquidity suppliers. However, these categories are not applicable in our context since our data is composed of small retail traders who do not possess the resources to open significantly large positions that might affect the liquidity of the asset traded, especially in the foreign exchange market.

require more information regarding the behavior of trade leaders. To elaborate, consider a group formed of informed and momentum traders. Momentum traders can be identified by their expected response to the previous day's price change, $P^k_{t-1} - P^k_{t-2}$. As such, momentum traders will use this information in their strategy, and we would expect to observe a positive correlation between the position direction and the direction of the previous price change. On the contrary, informed traders do not consider past price fluctuations, as their trades are forward looking by definition. Given these arguments, we define one additional rule that will be used in a joint test. Specifically, the momentum trading rule measures the propensity for a trade leader's position to react to the previous day's price change:

4. Momentum trading: $\theta^m_t = \begin{cases} \text{undefined}, & \text{if } \sum\limits_{k=1}^{K} \left|\Delta OI^k_t\right| = 0 \\ 1, & \text{if } \sum\limits_{k=1}^{K} \Delta OI^k_t (P^k_{o,t} - P^k_{t-1}) > 0 \\ 0, & \text{otherwise.} \end{cases}$

Trade leaders who adopt a momentum trading strategy would have $E(\theta^m_t) > 0.5$, while informed trade leaders would exhibit $E(\theta^m_t) = 0.5$. Similarly, contrarian trade leaders would exhibit $E(\theta^m_t) < 0.5$, while uninformed trade leaders would have $E(\theta^m_t) = 0.5$. Moreover, under the null hypothesis of no relation between position direction and price changes, θ^d_t and θ^m_t are independent and are both equal to one with a probability of 0.5. This null hypothesis can be formally expressed as H_0: $E[(1 - \theta^m_t)\theta^d_t] = 0.25$. It follows that one would expect informed trade leaders to perform at least as well as a trader placing random trades, such that $E[(1 - \theta^m_t)\theta^d_t] > 0.25$. This joint test identifies informed traders, where a trade is successful given that it was not placed in response to the previous day's price change.[6] Since the joint test offers some flexibility in how the null hypothesis is rejected for informed trade leaders, Fishe and Smith (2012) propose refining the test by imposing that $E(\theta^d_t) > 0.5$.

To summarize, we classify intraday trade leaders as follows:

- Informed: $E[(1 - \theta^m_t)\theta^d_t] > 0.25$ and $E[\theta^d_t] > 0.5$

- Momentum: $E[\theta^m_t] > 0.5$

[6]Fishe and Smith (2012) use the joint test, $E[(1 - \theta^m_t)\theta^d_t] = 0.25$, to identify both intraday informed traders and liquidity demanders, and apply an additional rule in order to differentiate between these two types of traders. However, given that our data set is composed of small retail traders whose positions are not large enough to impact liquidity, we simplify the identification process by arguing that the traders identified by the joint test are all informed intraday.

- Contrarian: $E[\theta_t^m] < 0.5$
- Uninformed: $E[\theta_t^m(1-\theta_t^d)] > 0.25$ and $E[\theta_t^d] < 0.5$.

4.3.3 Multiple Testing Correction

Since we are testing the predictive ability of thousands of trade leaders, the traditional levels of significance give rise to a multiple testing problem (Miller, 1981). To overcome this issue, we recalculate the probabilities obtained from the significance tests in order to retain a prespecified family-wise error rate, α. This correction decreases the likelihood of falsely rejecting the null hypothesis; Type I error. We use the framework proposed by Benjamini and Hochberg (1995) in order to control the false discovery rate (FDR), which is the percentage of rejected hypotheses that were falsely rejected.[7]

To understand how the FDR method works, assume that there are three types of trade leaders: informed (positive predictive ability), uninformed (negative predictive ability), and null traders (no predictive ability). Moreover, let π_0 denote the proportion of the population of trade leaders that are null. For each trade leader, $j = 1 \to n$, we compute a statistic, z_j, which has an asymptotic standard normal distribution under the null hypothesis of no predictive ability, and is centered away from zero under the two alternative hypotheses (informed and uninformed trade leaders). Suppose that for every trade leader, we employ a critical value denoted by c to test the one-sided hypothesis that the trade leader is informed. Hence, for trader j for whom the null hypothesis was rejected, the probability that this trader is actually null is given by:

$$\begin{aligned} FDR(c) =& \Pr(j \in \{null\} | z_j > c) \\ =& \frac{\Pr(z_j > c | j \in \{null\}) \Pr(j \in \{null\})}{\Pr(z_j > c)} \\ =& \frac{\Pr(z_j > c | j \in \{null\}) \pi_0}{\Pr(z_j > c)}. \end{aligned} \tag{4.6}$$

We choose the minimum value for c such that $FDR(c) \leq 0.05$, and we reject the null hypothesis for each trade leader with a z-statistic that exceeds c. As such, the

[7] While there are more stringent methods to correct for false discoveries, such as the Bonferroni correction, the FDR method has greater power; however at the cost of a higher potential occurrence of Type I errors (Shaffer, 1995).

group of trade leaders that is identified as informed is expected to contain no more than 5% who have been falsely discovered.

The *FDR* method has several important characteristics as highlighted by Fishe and Smith (2012). First, it adjusts the critical values based on the location of the informed trader. Hence, a larger critical value is chosen when the null and alternative hypotheses are close together, and a smaller value is chosen when the hypotheses are far apart. The second key feature of the *FDR* method is that the critical value, c, is independent of the number of traders, since it controls the proportion of null traders for whom the null hypothesis is rejected. Finally, the critical value is adjusted based on the proportion of traders who are null. As this proportion increases, the likelihood that a successful trader is simply lucky also increases. To account for this, the *FDR* method selects a larger critical value when the proportion of null traders increases.

4.4 Data and Measures

We use a data set from the popular eToro STP, which contains the trading activities of all participants during 2013. The STP records the details of every trade, including the opening and closing prices and timestamps, the leverage ratio used, the direction of the trade, as well as the asset being traded. We define a trade leader as a trader whose transactions were all entered manually into the STP during 2013. In other words, a trade leader is a trader who is original in his trades and who abstains from *explicitly* copying others through mirror trading. As such, we apply the latter criterion to select trade leaders from the entire population of eToro participants. In addition, we only study the trading activities of these traders in the 19 assets listed in Table 4.1, which include 16 currency pairs and three commodities.

The final sample contains over 700 thousand transactions executed by 41,072 position trade leaders, and over 1.7 million transactions executed by 48,691 intraday trade leaders. We calculate several descriptive statistics for each asset separately by averaging across all trades, and find that around 53% of transactions are in the three most liquid currency pairs, EUR/USD, USD/JPY, and GBP/USD. Moreover, 14 out of the 19 assets are net long positions, and the proportion of stop loss orders triggered is around double that of take profit orders across all assets. The table also shows that higher leverage is applied to more liquid currency pairs, such as

EUR/JPY, EUR/USD, and USD/JPY with ratios between 203 to one and 229 to one. Similarly, the debt-to-equity ratio shows that higher leverage is used in more liquid currency pairs such as, EUR/USD and USD/JPY, with ratios of around 127 and 148, respectively. Finally, we observe that the transactions in the more liquid assets have shorter durations compared to transactions in exotic currency pairs. The latter may be a consequence of using high levels of leverage when trading liquid assets, which magnifies price movements and decreases the time needed for a trade to potentially generate a desired profit amount.

In order to study the behavior of position informed, intraday informed, momentum, and contrarian trade leaders, we define several trading characteristics. The variable *Leverage* is the average leverage ratio used across all trades, and is a proxy for the risk appetite of a trade leader. The variables *TP* and *SL* are the proportions of a trade leader's transactions that are closed due to take profit and stop loss orders, respectively. The natural logarithm of the equity used by a trade leader, denoted by $\log(Equity)$, is an indication of how confident a trader is in his decision, such that a larger amount of equity signifies greater confidence. The *Long* variable is the proportion of a trade leader's transactions that are long positions, while the variable *Duration* is the average duration of trades measured in seconds. We use seconds to measure duration since trading on STPs is often very short term due to the roll over fees associated with keeping positions open overnight. Choosing a different time measure does not affect our results. The variable *Trades* is the number of trades executed by a trade leader during the period of study. Finally, the variable *Assets* is the number of different assets traded, and is an indication of the degree of specialization or diversification of a trade leader's strategy.

4.5 Results

4.5.1 Identifying Position Informed Trade Leaders

We apply the *FDR* method to identify position trade leaders who possess superior forecasting ability. Table 4.2 presents the number and proportion of position trade leaders that are identified to be informed in each of the 19 traded assets based on the position profits and daily trading profits rules, and using both the unconditional and HM tests. These numbers signify a lower bound of the true number of position informed trade leaders. By setting the *FDR* critical value equal to 5%, we require that at least 95% of those identified as informed to be truly informed.

Using the position profits rule, we assess the predictive ability of a trade leader based on the daily price changes of the traded asset. We identify a total of 20,403 unique position informed trade leaders under the unconditional test, which is around 50% of the position trade leader sample. To understand this figure, recall that the position profits rule considers unrealized profits on each day a position was open prior to it being closed. In other words, this rule measures the proportion of days a position trade was profitable. Thus, our result means that around 50% of position trade leaders exhibited unrealized gains more than half of the time their trades were open. Several of these individuals possess predicting ability in multiple assets, and are mostly concentrated in the major currency pairs such as EUR/USD, USD/JPY, GBP/USD, NZD/USD, AUD/USD, and USD/CHF. Nevertheless, this is expected since there are more individuals trading these major currency pairs relative to the exotic ones. When we apply the HM test on position profits, the number of unique position informed trade leaders drops to 46, making up only 0.11% of the sample. The reason for this significant drop is that the HM test is more stringent since it requires that trade leaders possess good predicting skills in both upward and downward trending markets. Our results suggest that very few position trade leaders exhibit unrealized gains more than half of the time, in both upward and downward trending markets. One may infer that very few of these individuals can appropriately predict price movements in both good and bad market conditions. The position informed trade leaders under the HM test are also found in the major currency pairs.

When we apply the daily trading profits rule, we are essentially assessing the predictive ability of a trader based on the final outcome of the trades. We identify a total of 21,541 unique position informed trade leaders (around 52% of the sample) based on the unconditional test, who are mostly found in the major currency pairs. This means that around half of position trade leaders realize a gain in more than half of their trades. When we apply the HM test, we identify 537 unique position informed trade leaders, which make up around 1.31% of the sample. This suggests that very few position trade leaders realize a gain in more than half of their trades, in both upward and downward trending markets. Again, the significant drop in the number of individuals identified as informed is due to the high threshold required by the HM test.

The results presented above clearly show that there is a significant difference in the way the unconditional and HM tests identify position informed trade leaders. The reason is that each rule defines informed traders differently. In the following section, we investigate the trading behavior of position informed trade leaders.

4.5.2 Position Informed Trade Leader Characteristics

In order to examine the characteristics of position informed trade leaders, we run a series of logistic models for each profit rule and identification test, where the binary dependent variable takes the value of one if the trader is identified as informed. The independent variables, discussed in section 4.4, capture the trading behavior of these individuals. Table 4.3 shows the results of the four logistic models. Regarding the position profits rule, the regression based on the unconditional test shows that there is a small but positive relationship between the average leverage ratio used and the likelihood of being informed, with a coefficient of 0.0015. This means that individuals whose positions exhibit an unrealized gain more than half of the time are slightly more aggressive in their strategies, which suggests that leverage plays a key role in allowing these traders to benefit from very small price swings. The *TP* variable is statistically significant with a coefficient of around -0.37. To explain this, recall that under the position profits rule we are assessing the predictive ability of a trade leader for each day the trade remained open. In other words, we are estimating the *proportion of days* of a trader's open trades that exhibit an unrealized gain. As such, a take profit order would trigger a winning trade to be closed, which decreases (or limits) the overall number of days where a trade is showing an unrealized gain. Consequently, a trader would have a lower proportion of days with winning trades, leading to a lower likelihood of being informed given the definition of informed trading under the position profits rule. With respect to the *SL* variable, we also report a significant and negative relationship with a coefficient of -0.51. One explanation for this is that position trade leaders may be choosing stop loss levels that are very close to the current market price in order to avoid large losses. Given that a position is typically opened with a negative net profit due to the bid-ask spread, any slight change in price, coupled the magnification effect of leverage, would trigger the stop loss limit. While a trader's strategy may be to use stop loss orders in order to minimize downside risk, accepting many small losses increases the aggregate number of days where a trader is experiencing a loss. This translates into a lower likelihood of being informed under the position profits rule. In support of our argument, Table 4.1 shows that the proportion of trades closed due to stop loss limits ranges between 14% and 31% across all assets, which is around twice the figures reported for take profit orders. This clearly indicates that there is a higher probability for a stop loss order to be triggered relative to a take profit order. Regarding the amount of equity invested, we report a coefficient of -0.106 for the variable log(*Equity*). This indicates that position informed trade leaders use relatively smaller amounts of their capital in each trade, which is consistent with a strategy where a trader is willing to accept multiple small losses in hopes of winning big. We find a negative relationship between the *Long* variable and the likelihood of being informed, which means that position informed trade leaders typically execute more short trades. We find that informed individuals have shorter average trade durations as indicated by the coefficient of the *Duration* parameter, which is equal to -8.7e^{-7}. While this figure may seem very small, recall that *Duration* measures the number of seconds a trade is kept open. To put this into perspective, keeping a trade open for one day (86,400 seconds) decreases the likelihood of being position informed by around 7.5%. The total number of trades executed, given by the variable *Trades*, also has a significant and negative relationship with being informed. This suggests that position informed trade leaders execute fewer trades, which may be an indication that they take into account trading costs when optimizing their strategies. As for the variable *Assets*, the coefficient is positively significant and equal to 0.34, meaning that position informed trade leaders seek trading opportunities in multiple assets. The pseudo R^2 for this model is 12.34%.

When we apply the more stringent HM test, the *Leverage*, *TP*, and log(*Equity*) parameters turn insignificant. This may be due to the fact that the HM test identifies very few position informed trade leaders (46 out of 41,072), which may not be sufficient to make proper inferences about the characteristics of these individuals. Nevertheless, we find that the *SL* parameter turns positive with a coefficient of 1.76. This suggests that these informed individuals apply stop loss limits in a manner that decreases the number of days a position is exhibiting a loss. The *Long* parameter remains negative and significant with a coefficient of -1.07, while the coefficient for *Duration* turns positive. The latter indicates that traders who are identified as position informed in both upward and downward trending markets tend to have longer trade durations. Moreover, these informed individuals trade more frequently as indicated by the *Trades* coefficient of 0.002, and seek trading opportunities in multiple assets as shown by the positive coefficient of the *Assets* parameter. Finally, the pseudo R^2 for this model is 18.21%. Given the low proportion of informed trade leaders under the HM test, the characteristics presented above should be taken with a grain of salt.

Next, we examine the trading characteristics of position informed trade leaders under the daily trading profits rule. Starting with the unconditional test, we find that *Leverage* has a coefficient estimate of 0.0015, indicating a positive impact on the likelihood of being position informed. This is similar to our initial finding, where leverage allows individuals to benefit from small price swings. Regarding limit orders, we find that *TP* has a positive effect with a coefficient of around 1.69, while *SL* has a negative effect with a coefficient of -4.08. To understand these results, recall that the daily trading profits rule assesses the predicting ability of a trader based on the final outcome of the trades, and not on the daily changes in price levels. As such, a take profit order is triggered when the position has made a profit, indicating that the trade was successful and that the trader made a correct prediction. Conversely, a stop loss order is triggered when the position exhibits a loss, which occurs when the price moves adversely to the trader's prediction. It follows that a take profit (stop loss) order is triggered when the trader's prediction is correct (false), thus increasing (decreasing) the likelihood of being informed. We report a negative coefficient of -0.15 for log(*Equity*), which is similar to what we found in our initial analysis. Regarding the *Long* parameter, we report a significant and positive coefficient of around 0.15, which means that informed traders have more accurate predictions when they are buying an asset relative to when they are selling one. We find that *Duration* has a positive effect on being position informed, meaning that these individuals keep trades open for a longer period until the market price reaches their target price. Similar to our initial analysis, we report a negative coefficient for the *Trades* parameter, and a positive coefficient for the *Assets* parameter, indicating that position informed trade leaders execute fewer trades in multiple assets. The pseudo R^2 for this model is 48.1%, which indicates that the model has a good fit.

Finally, when we apply the logistic model to the results of the HM test under the daily trading profits rule, we find that those identified as informed tend to use less leverage, meaning that these trade leaders implement more conservative strategies. Regarding limit orders, we find a positive coefficient of 0.96 for the *TP* parameter and a negative coefficient of -4.09 for *SL*, which are results similar to those obtained under the unconditional test. The log(*Equity*) parameter has a positive effect on the likelihood of being identified as position informed, with a coefficient of 0.49, which may be an indication that these individuals are aware of their superior forecasting ability, such that they are confident in investing more of their capital in each trade. We also find that position informed trade leaders engage more in short selling as indicated by the negative *Long* coefficient of -1.05. Contrasting this with the positive figure obtained under the unconditional test, this suggests that these informed individuals use short selling effectively as they are able to differentiate between upward and downward trending markets. The duration of a trade has a positive effect, which is similar to what was reported under the HM test based on position profits. In addition, we find that position informed traders under the HM test trade more frequently and in multiple assets as indicated by the positive coefficients of 0.01 and 0.03 for the *Trades* and *Assets* parameters, respectively. The pseudo R^2 for this model is also high and equal to 48.1%.

We focus the discussion on the results of the daily trading profits rule due to the superior fit of the models, and because realized profits represent the ultimate decision of a trader (Leuthold et al., 1994). The differences in trading characteristics presented above explain why a trade leader is identified as informed under one identification test and not the other. For instance, informed traders under the unconditional test are found to use more leverage compared to those under the HM test. Given the definitions of these tests, this means that the use of leverage plays a detrimental role in the performance of traders when the market changes direction. Hence, using less leverage allows informed traders to avoid large losses when the market changes direction. Similarly, the amount of equity invested by informed traders under the HM test is relatively larger indicating that these individuals are more confident about their predictions, considering the state of the market. Moreover, these individuals use short selling profitably, which is why they are identified as informed even in downward trending markets.

The above analysis shows that each profit rule and identification test identifies a different group of position informed trade leaders with different trading characteristics. In the following section, we use the *FDR* method to identify intraday informed, momentum, contrarian, and uninformed trade leaders.

4.5.3 Identifying Intraday Informed Trade Leaders

We use the *FDR* method using a 95% confidence interval and identify intraday trade leaders as informed, momentum, contrarian, or uninformed based on the rules defined in section 4.3.2. One point we highlight here is that a trader may be identified differently depending on which asset is being examined. For example, a trade leader may be identified as informed in the EUR/USD currency pair, but uninformed in oil trading. This means that a trader possess superior predicting ability only in a specific asset, which raises the question of how to classify this individual. As a remedy to this issue, we adopt a simple arithmetic approach where a trade leader is exclusively identified as one of the four types depending on how he is predominantly identified across all 19 assets. To illustrate, if a trader is found to be informed in the EUR/USD and GBP/USD currency pairs, but as a contrarian in the EUR/JPY currency pair, then this trade leader is exclusively identified as informed. The number and proportion for each type of trade leader in each of the 19 traded assets are presented in Table 4.4.

Given the rules defined in section 4.3.2, we identify 7,354 unique intraday informed trade leaders, which constitute around 15.1% of the sample. These individuals are mostly concentrated in major currency pairs such as EUR/USD, USD/JPY, GBP/USD, and NZD/USD. Regarding momentum and contrarian trading, we find that 23,903 (around 49%) and 14,195 (around 29%) trade leaders follow these strategies, respectively. Again, we find that the major currency pairs exhibit the highest number of traders following these strategies. Finally, we identify only 147 intraday uninformed trade leaders, which is relatively low compared to the number of informed traders in the sample. Given these figures, it is clear that there is a significant number of trade leaders who possess the ability to predict future price changes.

4.5.4 Intraday Informed Trade Leader Characteristics

We study the trading characteristics of intraday trade leaders by employing three separate logistic models, where the binary dependent variable takes the value of one if the trader is identified as informed, momentum, or contrarian, respectively. The independent variables are the same ones used earlier. We present the results in

Table 4.5.

Starting with intraday informed trade leaders, we find that these individuals tend to use slightly lower leverage ratios as indicated by the *Leverage* coefficient of -0.0005. This suggests that these individuals are slightly more conservative relative to other types of intraday traders. With respect to limit orders, we report a positive coefficient of 1.14 for *TP*, and -4.43 for *SL*. This means that a take profit (stop loss) order is executed when the trade is showing a gain (loss), which consequently increases (decreases) the probability of being identified as intraday informed. The log(*Equity*) parameter has a coefficient of 0.07, indicating a positive relation to the likelihood of being informed. Hence, informed intraday traders are confident in their decisions such that they are willing to invest more of their equity in each trade compared to other traders. Furthermore, we find that intraday informed individuals trade more successfully in short positions compared to long ones, as indicated by the negative *Long* coefficient of -0.27. The duration of trades for intraday informed traders is typically longer, which is similar to our findings for position informed traders under the HM test. In addition, we find that informed individuals trade more frequently and in multiple assets as indicated by the positive coefficients of 0.0006 and 0.04 for the *Trades* and *Assets* parameters, respectively. The pseudo R^2 for this model is equal to 20.93%, which indicates a good model fit.

Next, we examine but very briefly discuss the trading behavior of both momentum and contrarian trade leaders because 1) these traders are not the main focus of this study, 2) the logistic models are a poor fit, and 3) almost all coefficient estimates in the two models exhibit the same signs, hence we avoid repeating the discussion. We begin our analysis with the *Leverage* parameter, where we report a small but significant coefficient of 0.0008 for momentum traders, while this parameter is statistically insignificant for contrarian traders. Both momentum and contrarian trade leaders exhibit negative *TP* coefficients of -0.36 and -1.12, respectively. Given that the *TP* coefficient for intraday informed traders is positive, this suggests that take profit orders are associated with informed trading strategies. Both momentum and contrarian trade leaders use stop loss orders as indicated by their respective *SL* coefficients of 0.3 and 0.99. This is in contrast to intraday informed traders who are around 83 times less likely to have a stop loss order triggered. Hence, informed traders either avoid using stop loss orders, or place wider stop loss limits, which are less likely to be triggered throughout the life of a trade. The log(*Equity*) parameter has a negative coefficient of around -0.03 and -0.04 for momentum and contrarian traders, respectively, which suggests that both types of traders use relatively less of their capital in each trade. With respect to the *Long* parameter, we find that the trades executed by momentum traders are predominantly long, while those executed by contrarian traders are predominantly short. This is an indication that the overall trend across all assets was upward during the period of study. The *Duration* parameter indicates that both momentum and contrarian traders generally have shorter trade durations as compared to intraday informed traders. Moreover, we find that momentum trade leaders execute slightly fewer trades and trade in multiple assets, as indicated by the *Trades* and *Assets* coefficients of -0.0016 and 0.05, respectively. Both of these parameters are statistically insignificant for contrarian trade leaders. Finally, the pseudo R^2 for the momentum and contrarian models equals 1.6% and 4.88%, respectively, indicating that these models have a poor fit.

4.6 Conclusion

In this paper, we investigate the predictive ability of individual foreign exchange and commodities traders under a scopic regime. We use a data set from the highly popular eToro STP, and classify over 700 thousand transactions by 41,072 position trade leaders, and over 1.7 million transactions by 48,691 intraday trade leaders during 2013, in 16 currency pairs and three commodities. We adopt some of the methods applied in the literature to identify trade leaders as position informed, intraday informed, momentum, contrarian, and uninformed.

For position informed trade leaders, we focus on the daily trading profits rule — because the models have a superior fit, and realized profits represent the ultimate decision of a trader (Leuthold et al., 1994) — and summarize the findings as follows. When we apply the unconditional test, we find that around 50% of position trade leaders are informed, which means that half of the position traders have profitably executed more than 50% of their trades. These individuals 1) tend to use slightly more leverage, 2) apply take profit and stop loss orders to realize gains and minimize losses, respectively, 3) use less of their equity in each trade, 4) are more successful in long positions relative to short selling, 5) have longer trade durations, 6) trade less frequently, and 7) seek trading opportunities in multiple assets.

Next, we apply the HM test in order to identify individuals who are able to correctly predict future price movements in both upward and downward trending markets, and find that only 1.31% of position trade leaders possess this skill. This figure is similar to the finding by Linnainmaa (2010), who shows that around 1.2% of investors possess genuine trading skills. Moreover, this also adds to the finding of Hayley and Marsh (2015), who show that even the most experienced traders still underperform. Our analysis shows that these informed trade leaders 1) tend to use lower leverage ratios compared to the total sample including those identified as informed under the unconditional test, 2) apply take profit and stop loss orders to realize gains and minimize losses, respectively, 3) use more of their equity, which is a sign of confidence in their decisions, 4) use short selling profitably, 5) have longer trade durations, 6) trade more frequently, and 7) trade in multiple assets.

With respect to intraday trade leaders, we find that these individuals constitute around 15% of the intraday sample. Moreover, we find that intraday informed trade leaders 1) use slightly lower leverage ratios, 2) employ take profit and stop loss orders like position informed traders to realize gains and minimize losses, respectively, 3) use more of their equity in each trade, 4) are able to short sell consistently and profitably, 5) have relatively longer trade durations, 6) trade more frequently more, 7) and trade in multiple assets. These characteristics are similar to those of traders identified as position informed based on the daily trading profits rule under the HM test.

Our findings show that there is a positive relation between the degree of information transparency and the prospects of informed trading in the short term. We show that, although many trade leaders can predict price changes in a consistent manner in only one state of the market, very few individuals possess the skill to distinguish between different market states. Further research is required in order to investigate whether this short-term outlook and inability to recognize shifts in the market is due to behavioral biases such as herding, the disposition effect, overconfidence, or limited attention. Nevertheless, the evidence presented shows that STPs offer a source of valuable information, and that these platforms have the potential of creating short term information differentials in the foreign exchange as well as the commodities markets. This argument is in agreement with the evidence presented by Nolte and Nolte (2016), who show that the information contained in the order flow of individual foreign exchange traders may be used to explain, as well as forecast short-term price changes.

Investors who allocate their capital to trade leaders should be aware of this short-termism, and should diversify their investments accordingly in order to avoid large losses when market conditions change. Hence, investors can either take an active management approach and invest with trade leaders who possess predictive ability in only one market state, or take a passive approach and invest with those who possess the ability to predict price changes under any market condition. While our study focuses on the predictive ability of traders, further research is required in order to examine the overall profitability of these individuals in order to determine whether they add any value in absolute terms. Moreover, as social trading increases in popularity and becomes an integral component of financial markets, an intriguing puzzle is to analyze whether the value provided by these platforms will cease to exist as individuals take advantage of the information contained in order flow data.

Bibliography

Abbey, B. S. and Doukas, J. A. (2012). Is technical analysis profitable for individual currency traders? *Journal of Portfolio Management*, 39(1):142–150.

Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2):773–806.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2):785–818.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1):289–300.

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies*, 5(4):637–667.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5):992–1026.

Conrad, J. and Kaul, G. (1998). An anatomy of trading strategies. *Review of Financial Studies*, 11(3):489–519.

Covrig, V. and Melvin, M. (2002). Asymmetric information and price discovery in the fx market: does tokyo know more about the yen? *Journal of Empirical Finance*, 9(3):271–285.

Cressie, N. (1980). Relaxing assumptions in the one sample t-test. *Australian Journal of Statistics*, 22(2):143–153.

Curcio, R., Goodhart, C., Guillaume, D., and Payne, R. (1997). Do technical trading rules generate profits? conclusions from the intra-day foreign exchange market. *International Journal of Finance & Economics*, 2(4):267–280.

De Roon, F. A., Nijman, T. E., and Veld, C. (2000). Hedging pressure effects in futures markets. *The Journal of Finance*, 55(3):1437–1456.

Dewally, M., Ederington, L. H., and Fernando, C. S. (2013). Determinants of trader profits in commodity futures markets. *The Review of Financial Studies*, 26(10):2648–2683.

Doering, P., Neumann, S., and Paul, S. (2015). A primer on social trading networks— institutional aspects and empirical evidence. *Working Paper. Presented at EFMA Annual Meetings 2015.*

Evans, M. D. D. and Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, 110(1):170–180.

Fama, E. F. and French, K. R. (1987). Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. *The Journal of Business*, 60(1):55–73.

Fan, M. and Lyons, R. K. (2003). Customer trades and extreme events in foreign exchange. *Essays in Honour of Charles Goodhart*, 2:160–179.

Fishe, R. P. and Smith, A. D. (2012). Identifying informed traders in futures markets. *Journal of Financial Markets*, 15(3):329–359.

Frankel, J. A. and Froot, K. A. (1987). Using survey data to test standard propositions regarding exchange rate expectations. *The American Economic Review*, 77(1):133–153.

Froot, K., Arabadjis, J., Cates, S., and Lawrence, S. (2011). How institutional investors frame their losses: Evidence on dynamic loss aversion from currency portfolios. *The Journal of Portfolio Management*, 8(1):1–9.

Goodhart, C. (1988). The foreign exchange market: A random walk with a dragging anchor. *Economica*, 55(220):437–460.

Hartzmark, M. L. (1987). Returns to individual traders of futures: Aggregate results. *The Journal of Political Economy*, 95(6):1292–1306.

Hartzmark, M. L. (1991). Luck versus forecast ability: Determinants of trader performance in futures markets. *The Journal of Business*, 64(1):49–74.

Hayley, S. and Marsh, I. W. (2015). Do retail fx traders learn? *Working paper*.

Henriksson, R. D. and Merton, R. C. (1981). On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills. *The Journal of Business*, 54(4):513–533.

Hicks, J. R. (1946). *Value and capital: an inquiry into some fundamental principles of economic theory*. Oxford: Clarendon Press, 2nd edition.

Hirshleifer, D. (1988). Residual risk, trading costs, and commodity futures risk premia. *Review of Financial Studies*, 1(2):173–193.

Iwatsubo, K. and Marsh, I. W. (2014). Order flows, fundamentals and exchange rates. *International Journal of Finance & Economics*, 19(4):251–266.

Keynes, J. M. (1930). *A Treatise on Money: In 2 Volumes*. Macmillan & Company.

Knorr Cetina, K. (2003). From pipes to scopes: The flow architecture of financial markets. *Distinktion: Scandinavian Journal of Social Theory*, 4(2):7–23.

Kolb, R. W. (1992). Is normal backwardation normal? *Journal of Futures Markets*, 12(1):75–91.

Leuthold, R. M., Garcia, P., and Lu, R. (1994). The returns and forecasting ability of large traders in the frozen pork bellies futures market. *The Journal of Business*, 67(3):459–473.

Linnainmaa, J. T. (2010). Do limit orders alter inferences about investor performance and behavior? *The Journal of Finance*, 65(4):1473–1506.

Linnainmaa, J. T. (2011). Why do (some) households trade so much? *The Review of Financial Studies*, 24(5):1630–1666.

Lyons, R. K. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics*, 39(2):321–351.

Lyons, R. K. (1997). A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, 42(3):275–298.

Lyons, R. K. (2001). *The microstructure approach to exchange rates*. MIT Press.

MacDonald, R. and Marsh, I. W. (1996). Currency forecasters are heterogeneous: confirmation and consequences. *Journal of International Money and Finance*, 15(5):665–685.

MacDonald, R. and Marsh, I. W. (2004). Currency spillovers and tri-polarity: a simultaneous model of the us dollar, german mark and japanese yen. *Journal of International Money and Finance*, 23(1):99–111.

MacDonald, R., Menkhoff, L., and Rebitzky, R. R. (2009). Exchange rate forecasters' performance: Evidence of skill? *Working paper*.

Mahani, R. and Bernhardt, D. (2007). Financial speculators' underperformance: Learning, self-selection, and endogenous liquidity. *The Journal of Finance*, 62(3):1313–1340.

Mark, N. C. (1995). Exchange rates and fundamentals: Evidence on long-horizon predictability. *The American Economic Review*, 85(1):201–218.

Marsh, I. W. and O'Rourke, C. (2005). Customer order flow and exchange rate movements: is there really information content? *Working paper, Cass Business School*.

Melvin, M. and Shand, D. (2011). Active currency investing and performance benchmarks. *Journal of Portfolio Management*, 37(2):46–59.

Menkhoff, L. and Taylor, M. P. (2007). The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature*, 45(4):936–972.

Miller, R. G. (1981). *Simultaneous Statistical Inference*. Springer, 2nd ed edition.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Nolte, I. and Nolte, S. (2012). How do individual investors trade? *The European Journal of Finance*, 18(10):921–947.

Nolte, I. and Nolte, S. (2016). The information content of retail investors' order flow. *The European Journal of Finance*, 22(2):80–104.

Norman, D. J. (2009). *CFDs: The Definitive Guide to Contracts for Difference*. Harriman House Limited.

Odean, T. (1998a). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Odean, T. (1998b). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, 53(6):1887–1934.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5):1279–1298.

Osler, C. L. (2003). Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis. *The Journal of Finance*, 58(5):1791–1819.

Park, C.-H. and Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, 21(4):786–826.

Peck, A. E. (1980). The role of economic analysis in futures market regulation. *American Journal of Agricultural Economics*, 62(5):1037–1043.

Peiers, B. (1997). Informed traders, intervention, and price leadership: A deeper view of the microstructure of the foreign exchange market. *The Journal of Finance*, 52(4):1589–1614.

Pojarliev, M. and Levich, R. M. (2010). Trades of the living dead: style differences, style persistence and performance of currency fund managers. *Journal of International Money and Finance*, 29(8):1752–1775.

Shaffer, J. P. (1995). Multiple hypothesis testing. *Annual Review of Psychology*, 46(1):561–584.

Wang, C. (2001). Investor sentiment and return predictability in agricultural futures markets. *Journal of Futures Markets*, 21(10):929–952.

Table 4.1: **Descriptive Statistics of Assets Traded During 2013.** The following table shows descriptive statistics of the 19 assets that were traded by trade leaders during 2013 on eToro. These parameters include the following. *Trades* is the number of trades in the underlying asset. *% of Total Trades* is the proportion of trade executed in the asset relative to the total number of trades. *% Long* is the proportion of trades that are long positions. *% TP* and *% SL* are the proportions of trades that are take-profit and stop-loss orders, respectively. *Equity* and *Leverage* are the mean dollar amount of equity and leverage used in each trade, respectively. *Trade Size* is the average trade size in dollar amount. *Debt/Equity* is the mean debt-to-equity ratio, and *Duration* is the average duration of a trade measured in days.

Position Trades	=	700,538
Position Trade Leaders	=	41,072
Intraday Trades	=	1,775,023
Intraday Trade Leaders	=	48,691

Currency 1	**AUD**	**AUD**	**CAD**	**CHF**	**EUR**	**EUR**	**EUR**	**EUR**	**EUR**	**EUR**	**GBP**	**GBP**	**NZD**	**USD**	**USD**	**USD**	**Oil**	**Gold**	**Silver**
Currency 2	**JPY**	**USD**	**JPY**	**JPY**	**AUD**	**CAD**	**CHF**	**GBP**	**JPY**	**USD**	**JPY**	**USD**	**USD**	**CAD**	**CHF**	**JPY**			
Trades	23,764	134,626	12,082	32,190	33,808	17,091	33,591	27,230	164,005	771,634	77,241	233,472	140,330	72,894	86,176	322,286	60,843	174,130	58,168
% of Total Trades	0.95	5.41	0.49	1.29	1.36	0.69	1.35	1.09	6.58	31	3.10	9.37	5.63	2.93	3.46	12.94	2.44	7.0	2.34
% Long	57.86	58.17	63.65	30.42	69.45	46.15	79.60	60.76	52.54	48.97	50.52	53.75	47.10	52.32	72.31	56.15	57.54	64.56	76.69
% TP	11.50	12.8	12.51	13.44	14.17	12.46	10.85	12.27	14.45	14.28	13.14	13.58	13.96	11.0	13.0	16.14	9.74	9.35	8.36
% SL	27.28	21.31	25.23	26.26	26.59	26.11	16.40	18.94	29.60	21.86	30.53	23.06	16.84	14.14	19.4	21.43	20.96	24.31	20.92
Equity	116.75	132.43	79.65	104.94	88.03	66.05	89.25	76.25	120.60	109.70	90.89	127.16	110.65	92.62	116.83	102.18	87.42	137.49	79.7
Leverage	164	185.93	150.24	150.45	150.31	148.22	145.29	107.60	222.84	203.15	182.92	179.99	166.39	167.22	159.93	229.64	65.63	70.3	59.14
Trade Size	13,996	15,028	5,113	6,993	7,089	4,913	8,628	5,462	12,934	14,127	10,209	12,675	9,744	10,442	11,045	15,241	5,682	9,624	4,702
Debt/Equity	118.88	112	63.72	65.64	79.53	73.38	95.67	70.64	106.24	127.78	111.32	98.8	87.06	111.74	93.55	148.16	64.0	69.0	58.0
Duration	0.80	0.93	0.85	1.6	0.69	0.82	1.63	1.03	0.42	0.68	0.60	1.09	0.98	0.93	0.95	0.40	0.69	0.87	1.99

Table 4.2: **Position Informed Trade Leaders Identified Using the *FDR* Method.** The following table shows the number of position informed trade leaders who are identified to be significant by the false discovery rate method when the critical value of a one-sided test is set at the 5% level of significance. The table reports the number of position informed trade leaders for both the unconditional and HM tests and shows the percentage of informed relative to the total number of trade leaders in each of the 19 assets in the sample. The total number and percentage of unique position informed trade leaders are also reported.

	Position profits				Daily trading profits			
	Unconditional test		HM test		Unconditional test		HM test	
Asset	Count	% Traders	Count	% Traders	Count	% Traders	Count	% Traders
AUD/JPY	775	30.78	2	0.08	1,020	40.51	1	0.04
AUD/USD	2,084	28.43	11	0.15	2,725	37.18	60	0.82
CAD/JPY	508	28.4	2	0.11	818	45.72	0	0
CHF/JPY	969	26.37	0	0	1,441	39.21	1	0.03
EUR/AUD	1,104	30.11	2	0.05	1,580	43.1	3	0.08
EUR/CAD	785	30.57	1	0.04	1,039	40.46	1	0.04
EUR/CHF	1,299	26.09	3	0.06	2,005	40.28	5	0.1
EUR/GBP	1,219	30.54	1	0.03	1,577	39.5	8	0.2
EUR/JPY	2,009	31.91	2	0.03	2,383	37.86	37	0.59
EUR/USD	5,429	23.12	16	0.07	6,381	27.18	355	1.51
GBP/JPY	1,299	30.56	3	0.07	1,476	34.72	11	0.26
GBP/USD	2,916	27.77	10	0.1	3,500	33.33	110	1.05
NZD/USD	2,267	26.07	5	0.06	3,627	41.71	128	1.47
USD/CAD	1,843	27.38	4	0.06	2,945	43.76	30	0.45
USD/CHF	1,930	26.29	4	0.05	2,897	39.47	26	0.35
USD/JPY	3,851	29.91	6	0.05	4,578	35.55	61	0.47
Oil	831	17.74	3	0.06	1,499	32	3	0.06
Gold	1,182	14.66	0	0	1,997	24.76	26	0.32
Silver	1,011	16.01	1	0.02	1,747	27.67	5	0.08
Total unique	20,403	49.68	46	0.11	21,541	52.45	537	1.31

Table 4.3: **Position Informed Trade Leader Characteristics.** The following table presents the results of the logistic models for each of the profit rules and tests considered in the study. *Leverage* is the average leverage ratio used by the trade leader. The variables *TP* and *SL* are the percentages of a trade leader's transactions that are closed due to take-profit and stop-loss orders, respectively. The log(*Equity*) variable is the natural log of the average amount of equity used by the trade leader. The *Long* variable is the percentage of a trade leader's transactions that are long positions, while *Duration* is the average duration of trades measured in seconds. The variable *Trades* is the number of trades executed by a trade leader during the period of study. Finally, the variable *Assets* is the number of unique assets traded. We also report McFadden's Pseudo R^2 for each model.

	Position profits						Daily trading profits					
	Unconditional test			HM test			Unconditional test			HM test		
	Coef	S.E.		Coef	S.E.		Coef	S.E.		Coef	S.E.	
Leverage	0.0015	0.0001	***	-0.0011	0.0017		0.0015	0.0001	***	-0.0064	0.0007	***
TP	-0.3651	0.0408	***	-1.5665	1.1024		1.6878	0.0524	***	0.9646	0.1749	***
SL	-0.5149	0.0344	***	1.7630	0.6012	**	-4.0806	0.0552	***	-4.0878	0.3642	***
log(*Equity*)	-0.1055	0.0108	***	0.0992	0.1380		-0.1541	0.0142	***	0.4877	0.0386	***
Long	-0.1594	0.0278	***	-1.0669	0.5426	*	0.1534	0.0399	***	-1.0490	0.1758	***
Duration	-8.7e^{-7}	6.2e^{-8}	***	1.8e^{-7}	8.8e^{-8}	*	3.0e^{-7}	4.1e^{-8}	***	3.6e^{-7}	5.0e^{-8}	***
Trades	-0.0074	0.0004	***	0.0021	0.0004	***	-0.0032	0.0004	***	0.0119	0.0005	***
Assets	0.3386	0.0058	***	0.2628	0.0290	***	0.7378	0.0108	***	0.0343	0.0123	**
Intercept	-0.2892	0.0520	***	-8.7508	0.8304	***	-0.4282	0.0685	***	-5.2501	0.2309	***
Pseudo R^2	12.34%			18.21%			48.1%			41.76%		

Table 4.4: **Intraday Informed Trade Leaders Identified Using the *FDR* Method.** The following table shows the number of intraday informed trade leaders who are identified to be significant by the false discovery rate method when the critical value of a one-sided test is set at the 5% level of significance. The table reports the number of intraday informed, momentum, and contrarian trade leaders, and shows the percentage of each group relative to the total number of trade leaders in each of the 19 assets in the sample. The total number and percentage of unique intraday informed, momentum, and contrarian trade leaders are also reported.

	Intraday Informed		Momentum		Contrarian		Uninformed	
Asset	Count	% Traders	Count	% Traders	Count	% Traders	Count	% Traders
AUD/JPY	932	21.5	2,008	46.33	2,119	48.89	1,117	25.77
AUD/USD	2,431	23.45	3,925	37.86	4,239	40.89	1,734	16.72
CAD/JPY	636	21.34	1,465	49.14	1,434	48.1	828	27.78
CHF/JPY	1,078	21.32	2,242	44.33	2,388	47.22	1,252	24.76
EUR/AUD	1,173	19.97	2,554	43.48	2,590	44.09	1,342	22.85
EUR/CAD	774	19.65	1,919	48.72	1,880	47.73	1,048	26.61
EUR/CHF	1,395	23.88	2,616	44.78	2,803	47.98	1,399	23.95
EUR/GBP	1,414	26.32	2,355	43.84	2,572	47.88	1,154	21.48
EUR/JPY	1,939	14.17	6,150	44.94	6,253	45.69	3,837	28.04
EUR/USD	3,883	13.56	10,174	35.53	10,048	35.09	5,109	17.84
GBP/JPY	1,450	17.97	3,424	42.44	3,326	41.22	1,814	22.48
GBP/USD	3,039	18.85	5,458	33.85	6,447	39.99	2,629	16.31
NZD/USD	3,025	24.37	4,391	35.37	5,226	42.09	2,006	16.16
USD/CAD	2,588	27.01	3,917	40.88	4,360	45.51	1,761	18.38
USD/CHF	2,403	24.16	3,857	38.77	4,319	43.42	1,753	17.62
USD/JPY	3,559	18.35	8,138	41.95	7,800	40.21	4,351	22.43
Oil	1,111	18.21	1,864	30.55	2,266	37.14	1,005	16.47
Gold	1,141	11.69	2,872	29.43	3,168	32.47	1,168	11.97
Silver	917	14.33	2,441	38.13	2,197	34.32	1,055	16.48
Total unique	7,354	15.1	23,903	49.09	14,195	29.15	147	0.3

Table 4.5: **Intraday Trade Leader Characteristics.** The following table presents the results of the logistic models to examine the characteristics of intraday informed, momentum, and contrarian trade leaders. *Leverage* is the average leverage ratio used by the trade leader. The variables *TP* and *SL* are the percentages of a trade leader's transactions that are closed due to take-profit and stop-loss orders, respectively. The log(*Equity*) variable is the natural log of the average amount of equity used by the trade leader. The *Long* variable is the percentage of a trade leader's transactions that are long positions, while *Duration* is the average duration of trades measured in seconds. The variable *Trades* is the number of trades executed by a trade leader during the period of study. Finally, the variable *Assets* is the number of unique assets traded. We also report McFadden's Pseudo R^2 for each model.

	Intraday informed			Momentum			Contrarian		
	Coef	S.E.		Coef	S.E.		Coef	S.E.	
Leverage	-0.0005	0.0001	***	0.0008	0.0001	***	0.0001	0.0001	
TP	1.1434	0.0469	***	-0.3595	0.0392	***	-1.1174	0.0522	***
SL	-4.4251	0.0902	***	0.3035	0.0328	***	0.9870	0.0361	***
log(*Equity*)	0.0680	0.0133	***	-0.0263	0.0091	**	-0.0434	0.0104	***
Long	-0.2701	0.0449	***	0.2833	0.0264	***	-0.1883	0.0290	***
Duration	$1.2e^{-5}$	$1.4e^{-6}$	***	$-3.6e^{-6}$	$9.6e^{-7}$	***	$-3.5e^{-6}$	$1.1e^{-6}$	**
Trades	0.0006	0.0001	***	-0.0016	0.0001	***	-0.0001	0.0001	
Assets	0.0420	0.0035	***	0.0527	0.0029	***	0.0037	0.0031	
Intercept	-1.3350	0.0668	***	-0.4617	0.0465	***	-0.8914	0.0524	***
Pseudo R^2	20.93%			1.6%			4.88%		

Chapter 5

Conclusion and Future Work

The contributions of this PhD are both theoretical and empirical. In the first study, we examine herding behavior among 77,476 trade leaders during 2013 on the popular eToro STP. The main theoretical contribution is that the scopic regime, characterized by high information transparency and constant investor scrutiny, produces levels of, and persistence in herding behavior that exceed those found in a traditional financial environment. We use two herding metrics developed by Lakonishok et al. (1992) and Frey et al. (2014) in order to provide a range for the true level of herding among trade leaders. In general, we find that the level of herding for the entire sample of trade leaders lies between the lower LSV measure of 16.5% and the upper FHW measure of 23.9%. These levels exceed those reported in the literature for both institutional and retail traders in traditional financial environments. Moreover, we find that as the number of active trade leaders in a security increases, the level of herding decreases proportionally. This is due to higher herding levels in less traded assets, which is evidence of information cascades that motivate herding (Bikhchandani et al., 1992). Second, we find that trade leaders who use high leverage ratios tend to herd less, which suggests that these individuals are overconfident in their own skills and decisions (Scharfstein and Stein, 1990; Odean, 1998; Gümbel, 2005). Third, we examine the association between herding and trade size and find that the larger the trade size — the more a trader has to lose — the higher the likelihood of herding with the general consensus. This is related to the feeling of regret traders would experience had they invested differently from and underperformed their peers. One exception to this is the level of herding in the smallest trade sizes, which is high and may be the result of trade leader sophistication on this platform

(Doering et al., 2015). To elaborate, small trades may be regarded as an option for the trade leader to imitate others, such that one can increase exposure if the strategy is profitable, or simply cut losses should the strategy be unprofitable. Finally, we examine persistence in herding behavior by computing the mean contemporaneous and time-series correlations of purchase intensities based on the method used by Barber et al. (2009). We find a significant and almost perfect contemporaneous correlation of 98.5%, which further confirms our earlier findings. In addition, we report significant evidence on persistence in herding across several time horizons, which fades away very slowly compared to what is reported in the literature for retail traders in a traditional trading environment (Barber et al., 2009; Merli and Roger, 2013). This shows that a scopic regime increases the likelihood of constant and perpetual herding. Our findings support the notion of intentional herding, as individuals seek information from, and try to emulate the success of other participants on the platform by mimicking their current as well as historical trading activity.

In the second study, we test whether trade leaders on the eToro STP exhibit the disposition effect, which is understood as the tendency to realize gains and hold on to losses (Shefrin and Statman, 1985). Our theoretical contribution builds on the learning theory discussed by many academics in the literature (Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005; Dhar and Zhu, 2006; Chen et al., 2007; Boolell-Gunesh et al., 2009; Seru et al., 2010). Specifically, we argue that the scopic environment — which is rich in information and requires participants to disclose all their trading activities — erodes the disposition effect as trade leaders adjust for this bias by learning not only from their personal trades, but also from the trades of others. Hence, as information on order flow becomes more accessible, trade leaders learn from these "experiences" in order to adjust for the disposition effect. We use a sample from the eToro STP with over 2.6 million trades executed by 77,476 trade leaders in 2013. We adopt two empirical methods: the first, proposed by Odean (1998), requires the calculation of the disposition spread, which is the difference between the proportion of gains realized and the proportion of losses realized, and the second is based on the Cox proportional hazards model. Furthermore, we compare the results obtained for trade leaders on eToro to those of traders on a traditional online trading platform called Anonymous. Under both empirical methods, we find weaker evidence of the disposition effect in the scopic environment relative to the traditional financial setting, which suggests that high information transparency and constant reciprocal scrutiny erode this behavioral bias, although not completely. We argue that traders in a scopic environment learn at a faster rate compared to traders in a traditional financial setting; however, more work is needed in this respect. Another potential explanation for the weak evidence of the disposition effect in the scopic environment is that the constant scrutiny by investors may drive trade leaders to close losing positions with almost the same propensity of closing winning positions, in order to avoid holding unjustifiable paper losses. From a "best practice" viewpoint, some academics have proposed that brokerage firms should educate their clients about behavioral biases that may adversely impact their performance (Dhar and Zhu, 2006). Our study shows that, while this may be a commendable initiative on behalf of brokerage firms, simply increasing information transparency would allow individuals to efficiently learn on their own to avoid the disposition effect by observing the actions of others.

In the third study, we investigate the predictive ability of traders under a scopic regime, where individuals have access to high quality order flow data on a social trading platform. This social trading setting differentiates our study from earlier research done on the predictive power of technical analysis, which focuses solely on past price movements and a selection of technical indicators (Abbey and Doukas, 2012). Furthermore, it complements the work of Hayley and Marsh (2015) on the performance, and learning ability of currency traders in a traditional trading environment, and extends the findings of Nolte and Nolte (2016), who show that the information contained in the *aggregate* order flow of individual traders has significant predictive power. Our proposition is that, despite potential behavioral biases, an environment that is highly transparent regarding order flow information should increase the overall prospects of informed trading. To test this, we use a data set from the highly popular eToro STP and classify over 700 thousand trades executed by 41,072 position trade leaders, and over 1.7 million trades executed by 48,691 intraday trade leaders in 16 currency pairs and three commodities during 2013. We apply empirical methods similar to those developed by Henriksson and Merton (1981) and Fishe and Smith (2012) in order to identify trade leaders as either position informed, intraday informed, momentum, contrarian, or uninformed. In particular, we use two binary profit rules based on unrealized profits (position profits) and realized profits (daily trading profits), separately, to test whether position trade leaders are informed. Additionally, we apply for each profit rule an unconditional test and a conditional (HM) test similar to the method proposed by Henriksson and Merton (1981), where the former is a binomial test for the expectation of being profitable more than 50% of the time, and the latter tests whether traders are able to trade profitably in both upward and downward trending markets. Moreover, we analyze intraday profits and the relationship between position direction and past price movements in order to identify intraday trade leaders as either informed, momentum, contrarian, or uninformed. We use the false discovery rate (FDR) method with a 5% critical value to correct for the multiple-testing problem, which arises due to having thousands of test statistics (Benjamini and Hochberg, 1995). For position trade leaders, the unconditional test identifies around 50% of these individuals as informed; however, when we apply the HM test, this proportion drops between 0.11% and 1.31%. This suggests that, while many position traders can predict future price changes in one specific state of the market, very few possess predictive ability in both upward and downward trending markets. We examine the characteristics of position informed trade leaders using a series of logistic models. The models based on the daily trading profits rule have a superior fit, hence we focus the discussion on these results. Specifically, individuals identified as position informed under the unconditional test tend to use more leverage, apply limit orders to realize gains and limit losses, use less equity per trade, are more successful in long positions, have longer trade durations, trade less frequently, and trade in multiple assets. When we study the characteristics of traders identified as informed under the HM test, we find that these individuals use less leverage, employ limit orders, use more equity per trade, apply short-selling profitably, have long trade durations, trade more frequently, and trade in multiple assets. With respect to intraday trade leaders, we identify around 15%, 49%, 29%, and 0.3% of the sample as informed, momentum, contrarian, and uninformed, respectively. When we examine the characteristics of these types of traders, we find the highest explanatory power for the intraday informed model. In particular, we find that intraday informed trade leaders use relatively less leverage, employ limit orders, use more of their equity in each trade, are more successful in short-selling, have relatively longer trade durations, trade more frequently, and trade in multiple assets. Our findings show a positive relation between transparency regarding order flow data and the prospects of informed trading, at least in the short term. We find that, although the majority of trade leaders are consistently able to predict price changes in a specific state of the market, very few individuals possess the skill to distinguish between different market states. However, the evidence we present supports the idea that STPs offer a source of valuable information, and that these platforms have the potential of creating short term information differentials that can generate profitable opportunities in the foreign exchange as well as the commodities markets.

This thesis presents significant evidence on how the scopic environment influences trader behavior. We have shown that an environment, which encourages information transparency and allows constant reciprocal scrutiny by all participants leads to higher levels of, and persistence in herding behavior. Moreover, such an environment allows traders to learn not only from their personal past trades, but also from the trades of all other participants in order to adjust for the disposition effect. Trader behavior on STPs is significantly different compared to the behavior of traders in a traditional financial setting as presented in this thesis, and this can be attributed to technological innovation, which has considerably changed the online trading model. As such, technological innovation has an indirect impact on the behavior of traders. Consequently, one should expect the behavior of traders to change as new financial tools and features are introduced into the trading environment.

We briefly conclude by discussing future work we aim to undertake. While the first paper in this PhD dissertation examines herding behavior among trade leaders, another research puzzle is to investigate the *explicit* herding relationship between investors and trade leaders, which arises when investors opt to copy the future trades of trade leaders. The process of copying a trade leader, or terminating this relationship, is similar in concept to the dynamics of fund flows, which has been studied extensively. Some of the research questions that we aim to answer are: 1) What are the characteristics of the most popular trade leaders? 2) How does trade leader performance impact the number of copiers they have? 3) What are the events that drive an investor to terminate a copying relationship? 4) Do investors overreact to a trade leader's poor performance such that they terminate the copying relationship prematurely? To our knowledge, no research has been conducted to answer these questions, and one main reason for this is restricted access to data. Nevertheless, we are in the process of negotiating a non-disclosure agreement with a STP, which has agreed to provide us with the necessary data to proceed with such a study.

Another aspect of social trading we aim to investigate is the longevity of trade leader accounts. Since CFDs are based on margin trading and on excessive use of leverage, a prolonged period of bad performance may result in trade leaders closing their accounts completely — whether voluntarily or not. This event has consequences to investors, who may have invested a large portion of their capital in this socio-financial asset, which has suddenly ceased to exist. Thus, we aim to examine the factors that affect the longevity of trade leaders and the termination of their accounts. This study will require a data set that spans a longer period compared to the one we are currently using, which an anonymous STP has agreed to provide us.

A challenging objective for future research is to incorporate complex social data, such as discussion posts, into the financial framework. Hence, the richness of social trading information may require methodological contributions in order to better understand the performance and relationships between participants on STPs.

As stated earlier, technological innovation has an indirect impact on trader behavior. As the social trading environment evolves with technology, this dynamic will open up new avenues for exciting research, both theoretical and empirical.

Bibliography

Abbey, B. S. and Doukas, J. A. (2012). Is technical analysis profitable for individual currency traders? *Journal of Portfolio Management*, 39(1):142–150.

Barber, B. M., Odean, T., and Zhu, N. (2009). Systematic noise. *Journal of Financial Markets*, 12(4):547–569.

Benjamini, Y. and Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1):289–300.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5):992–1026.

Boolell-Gunesh, S., Broihanne, M.-H., and Merli, M. (2009). Disposition effect, investor sophistication and taxes: Some french specificities. *Finance*, 30(1):51–78.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M. (2007). Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors. *Journal of Behavioral Decision Making*, 20(4):425–451.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Doering, P., Neumann, S., and Paul, S. (2015). A primer on social trading networks— institutional aspects and empirical evidence. *Working Paper. Presented at EFMA Annual Meetings 2015.*

Feng, L. and Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, 9(3):305–351.

Fishe, R. P. and Smith, A. D. (2012). Identifying informed traders in futures markets. *Journal of Financial Markets*, 15(3):329–359.

Frey, S., Herbst, P., and Walter, A. (2014). Measuring mutual fund herding — a structural approach. *Journal of International Financial Markets, Institutions and Money*, 32:219–239.

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Gümbel, A. (2005). Herding in delegated portfolio management: When is comparative performance information desirable? *European Economic Review*, 49(3):599–626.

Hayley, S. and Marsh, I. W. (2015). Do retail fx traders learn? *Working paper*.

Henriksson, R. D. and Merton, R. C. (1981). On market timing and investment performance. ii. statistical procedures for evaluating forecasting skills. *The Journal of Business*, 54(4):513–533.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1):23–43.

Merli, M. and Roger, T. (2013). What drives the herding behavior of individual investors? *Finance*, 34(3):67–104.

Nolte, I. and Nolte, S. (2016). The information content of retail investors' order flow. *The European Journal of Finance*, 22(2):80–104.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *American Economic Review*, 80(3):465–479.

Seru, A., Shumway, T., and Stoffman, N. (2010). Learning by trading. *Review of Financial Studies*, 23(2):705–739.

Shapira, Z. and Venezia, I. (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance*, 25(8):1573–1587.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.